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Development and validation of the generative artificial intelligence appropriation (GAIA) Scale: A comprehensive measurement tool for assessing user engagement and utilisation

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ABSTRACT

Generative Artificial Intelligence Appropriation (GAIA) encapsulates how users adopt Generative Artificial Intelligence tools, adapt them according to their needs, and integrate them into their work. The rapid adoption of generative AI tools has demonstrated their transformative potential to effect significant improvements in the field of business management and change the work habits of their users. Considering the multitude of applicative possibilities offered by the technology, in addition to its nascence, there are significant concerns regarding how the technology can be utilised, necessitating GAIA assessment in the workplace. Existing instruments prove inadequate in providing a comprehensive measurement of GAIA. In response, this research adopts a mixed-method approach, comprising qualitative and quantitative insights from multiple studies. Drawing on multiple samples, this study develops and validates a second-order, reflective-reflective GAIA measure, comprising dimensions of integrative appropriation, adoptive appropriations, customised appropriation, interface appropriation and ethical appropriation. The research encompasses four studies with a distinctive focus on item generation, scale purification, scale refinement and nomological validation. The GAIA scale developed herein offers a robust and comprehensive measure that can be used to explicate, assess, and improve GAIA in the workplace.

1. Introduction

The digital era has marked the rapid emergence of artificial intelligence (AI) and its subset, machine learning, into our day-to-day lives (Dwivedi et al., 2023; Kumar et al., 2023 Thomas et al., 2024a). From the underlying technology in smartphones to the arrival of autonomous vehicles and retailers' personalised proficiencies, these progressions with tools like generative AI signify a gradual change in our technological structure (Saviano et al., 2025). Generative AI encapsulates a broad category of technologies that provide machine learning solutions, trained on extensive datasets and generate output in response to user prompts (Sætra, 2023). It leverages deep learning models to produce human-like content (Lim et al., 2023). With distinguished examples like Dall-E 2, GPT-4, and Copilot, Generative AI is rising as a technological trendsetter in the corporate sector. Generative AI is a collection of AI techniques that influence remnants from existing data for the creation of new and exclusive products. It includes the ability to generate numerous media forms like text, images, audio, code, and video (Gartner, 2022). By scrutinising and comprehending patterns in the accessible data, generative AI algorithms can produce outcomes that reflect creativity and innovation (Thomas et al., 2024a).

Generative AI has become more significant since late 2022, with the launch of OpenAI's ChatGPT (Dwivedi et al., 2023). Within two months of its launch, the platform boasted a 100-million active user base,

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catapulting it to the "fastest-growing consumer application in history" (Hu, 2023). In June 2023 alone, the website generated 1.6 billion visits (Duarte, 2023). This innovative chat-based item employs the Generative Pre-trained Transformer (GPT) large language model (LLM) to create advanced conversational capabilities. The technology influences its contributions (the data used and a user prompt) and experiences (communications with users to help "learn" new information and what's right or wrong) to create completely new content (Chui et al., 2022). Capgemini's recent research highlights this drive by emphasising that 96 % of organisations surveyed globally have identified generative AI in their boardroom debates. Even though this technology is still in its early stages of widespread adoption, an important 60 % of global executives expressed strong support for its incorporation from their leadership. However, with such rapidly evolving technologies, the focal point is no longer *who* uses the technology, but *how* people use the technology (Wirth et al., 2008). With this fundamental shift in ideology, appropriation of technology has come to occupy a more crucial role than the technology itself (Kummitha, 2020). Technological appropriation refers to how technologies are adopted, adapted and incorporated into a user's work practices (Bal et al., 2022).

Human agents, from passive entities, have morphed into active creators and users of technology (Moura and Bispo, 2020). More recent theoretical trends, like the sociomateriality perspective, also present technology and agency as mutual enablers, defining technology as a social object whose meaning is shaped by its use (Orlikowski and Barley, 2001). In the context of embracing novel technologies, the utilisation of generative AI can be examined from the structuration lens. Structuration theory attempts to recast structure and human agency as a mutually dependent duality, emphasising that in social contexts, the impact of advanced technology is contingent upon its utilisation and appropriation by users, rather than the technology itself (DeSanctis and Poole, 1994). Social Shaping of Technology theory (SST; Williams and Edge, 1996), in this regard, prioritises the social forces that incite technological change. Thus, the successful implementation of a technology now depends on its continued use (Benamar et al., 2020). Especially with technologies like Generative AI, which are evolving so rapidly, there is a need to shift focus from initial adoption to continued use, making investigation of its appropriation a more salient issue. Generative AI appropriation encapsulates the process through which users adopt Generative AI, adapt it according to their needs, and embed it into their everyday lives (Bar et al., 2016; Carroll et al., 2003; Dourish, 2003). Consequently, Generative AI's rise necessitates a quick and deeper look into its nuanced appropriation in organisations, especially at the individual level, considering that this is where technology usage occurs.

The current rush in Generative AI applications has prompted scholarship in different spheres, like health (Biswas, 2023), medicine (Dahmen et al., 2023), education (Lim et al., 2023; Lund and Wang, 2023), human resource management (Budhwar et al., 2023; Mendy et al., 2025), customer review (Koc et al., 2023), knowledge management (Thomas, 2024) and tourism (Carvalho & Ivanov, 2023), etc. However, most of the current literature leans towards conceptual, review, or opinion articles (Burger et al., 2023; Dwivedi et al., 2023; Lim et al., 2023), which leaves a significant gap in empirical research. Mainly, the adoption and appropriation of Generative AI by individuals and teams affirm consideration. Beyond mere technological adoption, the exact spirit of Generative AI's abilities is in its appropriation, in which the users are needed to investigate the post-management and to redesign the tool outside its envisioned usage. This aligns with the viewpoints of scholars such as Ylipulli et al. (2014) and Mifsud et al. (2015), who view appropriation as a user-centric customisation that vibrates with the impression that users may alter technology's use in a style that is not envisioned by its developers.

Based on this viewpoint, the current research on technology appropriation establishes three main inadequacies. The first is an important part of the research that accepts a qualitative type (Loh and Chib, 2022). While these studies give insight into participant behaviours towards their use of particular technologies, there is also the need for "quantitative studies of appropriation at the stage of conceptual definition" (Loh and Chib, 2022, p. 7). *On similar lines,* Wirth et al. (2008) *have also highlighted the need for expanding appropriation research beyond qualitative methodologies to quantitative types, considering they are more "accessible in terms of testing for validity and reliability" (p.609).* The second concern is the focus of analysis, noting that technology appropriation research has generally focused on group or organisational levels, neglecting individual technology usage (Kirk et al., 2015). Considering that technology is used primarily by individuals, and yet most appropriation research has concentrated on group and organisational levels, there exists a significant gap (Gaskin and Lyytinen, 2012). To gain a comprehensive understanding of how GAI is effectively utilised, it is essential to supplement studies at the group and organisational levels with research focusing on individual appropriation of GAI. The third inadequacy presents as an absence of reliable and validated measurement scales for appropriation, specifically at an individual level (Loh and Chib, 2022). Insights into the appropriation of a nascent technology like Generative AI are critical to determining its trajectory. Understanding how Generative AI is adopted as well as how outcomes are associated with its utilisation, necessitates measurement of Generative AI appropriation. Taken together, these inadequacies warrant the need for a new scale that can comprehensively assess Generative AI appropriation at the individual level.

The insights resulting from studying GAIA would provide a particular roadmap for business professionals and team leaders, directing them to the effective use of this AI tool. Proper appropriation of Generative AI can introduce a "domino" impact of improved productivity and collaboration, eventually endorsing a more efficient and innovative work environment through numerous divisions. The present paper, thus, addresses this research gap and presents a Generative AI appropriation (GAIA) scale that aims to ascertain how individual users adopt Generative Artificial Intelligence-based technologies, adapt them according to their needs, and integrate them into their daily work practices.

2. Theoretical background

Generative AI, a distinct class of AI technologies, holds tremendous potential to influence how we work (Thomas et al., 2024a; Davison et al., 2023; Lim et al., 2023). In a workplace laden with GAI, it is crucial to change our viewpoint from a deterministic approach to one that handles emergence. This means that GAI should be viewed as a creation whose functions and impacts are not predetermined, but rather influenced by people's decisions and usage (Brown et al., 2024). Consequently, we've drawn on two predominant theories in appropriation literature to conceptualise GAIA: Social Shaping of Technology (SST) theory (MacKenzie and Wajcman, 1999) and Adaptive Structuration theory (AST; DeSanctis and Poole, 1994).

The SST theory was developed to overcome the limitations of the primitive theology of 'technological determinism' (i.e., technology sculpts the society, but is itself not reciprocally influenced). SST, instead, prioritises the social forces that incite technological change (Williams and Edge, 1996). There are two main approaches to understanding the sociology of technology: micro and macro (Mackay and Gillespie, 1992). The micro-level approaches to SST give preference to the subject in lieu of the structure. A dominant ideology within the micro-level approach is that of social constructivism, which suggests that technologies are socially constructed. Technological objects materialise from a process of active choice and negotiation amongst groups. Social construction of technology (SCOT) (Pinch and Bijker, 1984) emphasises that technology has interpretative flexibility and can be credited with diverse connotations by distinct social actors. Throughout the *interpretative flexibility phase*, various social groups denoting diverse benefits appear and are involved in discussion around the technology. These groups may involve developers, users, policymakers, ethicists, and the local public, who have their viewpoints, prospects, and apprehensions relating to Generative AI. These different social groups also differ in the way they perceive the nature and application of this technology, leading to variability in interpretations (Zhou, 2022). Eynon (2021) notes that AI technologies constitute "a complex sociotechnical artefact that needs to be understood as a phenomenon constructed through complex social processes". They found a limited connection between different stakeholders in how they understand and conceptualise AI. From a SCOT perspective, this interpretative flexibility leads to variability in use cases. How people interact with Generative AI tools, their social context, and how they feel about their role concerning AI determines the way this technology will be used and deployed.

The sociomateriality perspective further underscores this notion, emphasising that technologies in a social context depend less on the technology itself and more on how they are used and appropriated by users (Kummitha, 2020). Thus, human agency is just as important as social structures to comprehend technology (Pinch and Bijker, 1984). So far, the sociology of technology has disregarded the subjective social appropriation of technologies. The extension of SST (Mackay and Gillespie, 1992) gives emphasis to this very notion, i.e., the way technological artefacts are appropriated by their users. As such, it is essential to recognise that GAI tools develop as a result of human interaction. GAI should be seen as a creation whose functions and effects are not predetermined, but rather shaped by people's decisions and use. The SST approach provides a framework to analyse the complex micro-level processes involved in the adoption of GAI, making it an important perspective to consider when discussing GAI.

To gain a comprehensive understanding of GAI adoption and its various use cases, this study also relies on DeSanctis and Poole's Adaptive Structuration Theory (Astrachan et al., 2014). This theory is a widely used framework that explains how users utilise a particular technology through structuration processes (Ko et al., 2021). The theory introduces the concept of appropriation, which refers to the processes through which users use technologies in different ways that align with their work requirements (DeSanctis and Poole, 1994). The theory emphasises that the impact of advanced information technologies depends on how well social and technological structures are jointly optimised (Booyse and Scheepers, 2024). When a technology is used and appropriated, it leads to improved processes and structures. This, in turn, furthers developments in the technology (Gefen and Straub, 2005). As a result, over time, both the technology and the way people interact with it are transformed.

Despite the recent advancements in Generative AI, prevailing discourse has been found lacking a strong theoretical basis, with several of the studies not discussing a theory of AI at all (Booyse and Scheepers, 2024). This insufficiency underlines the need to re-evaluate existing theories, develop new ones, or look at certain theories from a new lens to effectively address the specific challenges presented by GAI. Upon the emergence of a novel technology, like GAI, there often ensues a fervour surrounding its prospective positive impact on society, alongside apprehensions about the potential disruption of established societal frameworks (Budhwar et al., 2023). The dichotomous perceptions, both favourable and unfavourable, associated with technologies like GAI assume a significant role in their adoption and concurrent resistance (Brown et al., 2024). AST, although not yet utilised in the context of GAI, has the potential to provide valuable insights into the interaction between technology and established routines, specifically the interplay between IT systems and their users. The theory presents a feasible approach to study advanced information technologies, allowing information systems researchers to collectively examine technology, user, and task in context (Schmitz et al., 2016). At the core of AST is the concept of appropriation, which is essential to the integration and use of advanced information technologies. With GAI eliciting such widely opposing views, there arises a pressing question: "How do people use GAI?" Examining this through the lens of appropriation can yield important insights on human action in relation to technology artefacts from a micro-lens.

3. Literature review

The recent widespread global adoption of Generative AI has demonstrated that these tools hold the potential to effect significant change in the world (Stadler and Reeves, 2023). They can enhance productivity, offering significant gains in healthcare, banking, business management, information technology industries, tourism, etc. (Dwivedi et al., 2023). Generative AI is quickly changing work habits of users, making its adoption a priority agenda for managers, entrepreneurs and organisations (Ritala et al., 2023).

However, considering the multitude of applicative possibilities offered by the technology, in addition to its nascence, there are significant concerns regarding how the technology can be used in the workplace. To understand the ways in which Generative AI can be used by employees within an organisational setting to achieve strategic goals, an understanding of GAIA is necessary. To achieve this, we first detail the concept of technological appropriation and then use that as a basis to discuss the dimensionality of GAIA.

3.1. *Technological appropriation*

The conventional notion that technology is a static input that users either accept or reject is inadequate for understanding how users utilise the interactivity, flexibility, and empathic capacity of technology to generate value for themselves. Recent scholarship in the field of information systems recognises that in a technology-rich world, there is a need for "a deeper understanding of the experience of technology use" (Kirk et al., 2015). Orlikowski (2000, p. 408) explains, "when users choose to use a technology, they are also choosing how to interact with that technology." Human action is elemental to shaping the situated use of technology, and it is this use of technology that is posited as appropriation of the technologies. The concept of appropriation is essential for the continued use of an IT artefact after its initial adoption and, consequently, for its success.

Poole and DeSanctis (1989) introduced the appropriation concept as part of an adaptive structuring process, in an attempt to explain the causal effect of technology on human behaviour and resultant organisational outcomes. They define appropriation in terms of the mode in which users use, adapt, and reproduce a structure" (Poole and DeSanctis, 1990, p. 184). New technologies aimed at attaining organisational improvements are continually being advanced and adopted (Cascio and Montealegre, 2016). Realising the benefits of these advancements is largely dependent on how these technologies are deployed by users (Bal et al., 2022). Human actors are not merely acquiescent subjects who succumb to the diktats of technology (Mackay and Gillespie, 1992). Thus, appropriation is not a predetermined process that follows a straight line, but in fact, involves a continuous negotiation between human actors and developers concerning user needs and changing situations (Bar et al., 2016; Hussenot, 2008; Ylipulli et al., 2014). Technological appropriation can be studied at the micro-level, institutional level and global level. In this study, we limit ourselves to the operationalisation of GAIA at the individual level (micro-level).

3.2. *Generative AI appropriation- ADO framework*

GAIA can thus be understood as the process through which users adopt Generative AI, adapt it according to their needs, and embed it into their everyday lives (Bar et al., 2016; Carroll et al., 2003; Dourish, 2003). At a micro-level, appropriation is initiated when an individual decides to adopt a new technology (Benamar et al., 2020; Carroll et al., 2003). Adoption constitutes the decision of choosing to use a particular technology, and can be understood as an individual's interest in, and willingness to use, Generative AI. This decision to adopt is usually driven by individuals' perception of the difference the technology can make in their lives. Prior research on technology diffusion and new product development has focused heavily on adoption and acceptance (Kirk et al., 2015). However, according to Dey et al. (2013), adoption alone cannot ensure continued, effective use of the technology. In order for technologies to progress, there is a need to shift our focus beyond just adopting them (Bar et al., 2016). To be impactful, technologies must be appropriated to context. Appropriation, thus, is a richer construct that subsumes the concept of adoption, making adoption one of the primary dimensions of GAIA.

In addition to adoption, appropriation also involves decisions regarding customisation and idiosyncratic use of technology (Kirk et al., 2015). Various scholars have proposed that appropriating a technology (like Generative AI) is based on human actors trying to make sense of the novel technology (Mifsud et al., 2015; Ylipulli et al., 2014). This involves a deeper appraisal of Generative AI following its usage. Beaudry et al. (2005, p. 497) define appropriation in terms of "the extent to which an innovation is changed during its adoption and implementation" (Gaskin and Lyytinen, 2012). Accordingly, technology appropriation is also defined in terms of adaptation, essentially referring to an alteration or modification of the technology to meet users' needs.

Adaptation is centred on matching the technology with the user by encouraging an alteration of routines and habits, improving their abilities, and adjusting the technology to reach their goals (Zamani et al., 2022). Users can adapt the technology and tasks by reinterpreting the technology and its features. According to Hussenot (2008), appropriation can also involve redefining the technology, as part of the process of change, which is not in complete control of the developer. In other words, human actors may alter the intended usage of a technology, positing appropriation as a customisation of technology (Loh and Chib, 2019, 2022). Ylipulli et al. (2014) encapsulate this as a "molding of technologies by giving meaning to them" (Ylipulli et al., 2014, p. 3). Users may explore the myriad of possibilities associated with Generative AI, so they can "do new things in new ways" (Bar et al., 2016, p. 10). They may refashion the application, reprogram it, institute added functionality, invent unintended uses, or even develop new ways to derive maximum benefit. This experimentation can result in users adopting a technology or adapting their practices around it. Such innovative usage adaptation enables users to achieve more from technology than their creators originally intended (Dey et al., 2013). This experimentation can result in users reinventing GAI, making adaptation an important facet of GAI appropriation.

Further, innovating with AI technologies allows users to delineate new uses of GAI for completing tasks. While trying to do so, users become active participants who derive meaning from integrating technologies into everyday lives, social relationships and work (Ylipulli et al., 2014, p. 3). In this regard, appropriation occurs when the users "take possession" of a technology (Carroll et al., 2003). At the core of appropriation, thus, lies this process of creative re-negotiation, wherein users take the technological tool and "make it their own" (Bar et al., 2016). In fact, ownership emerges as a dominant theme among several appropriation definitions. Gaskin and Lyytinen (2012) posit that appropriation is akin to psychological ownership of technology wherein users selectively choose "which features of a technology to use and how to use them – effectively taking responsibility for the way a technology is used". For users, their use of the technology then becomes an important part of the way they work. Mifsud et al. (2015, p. 708) conceptualise appropriation as a behaviour in information systems research, particularly delineating it as "the way users integrate a technical tool into their organisational routines". Here, the idea is to use the tool/artefact in a way that can aid in the development of skills, knowledge and competencies (Lin et al., 2022). The integration of technology into everyday practices and tasks serves as a critical GAIA indicator, ensuring user retention. Without embedding, technologies can be disappropriated just as swiftly as they were adopted. Hence, integration constitutes an important dimension essential to defining and operationalising GAIA.

Further, as the user engages with a technology, the user modifications that result may or may not be aligned with the spirit of the technology (DeSanctis and Poole, 1994), When a technology is used in a manner consistent with its intended functionality, it is characterized as a faithful appropriation of technology (Chin et al., 1997). When a user uses the technology in a manner that is inconsistent with its intended functionality, it is referred to as an ironic appropriation of technology. When the conceptualisation of appropriation was advanced, researchers believed that for technologies to have their intended impact, they must be faithfully appropriated (Poole and DeSanctis, 1989). However, the flexible nature of modern-day technologies makes them well-suited for innovative uses beyond their original design. In fact, novel unintended functionalities may be uncovered when technologies are used for purposes other than those envisioned by developers and managers (Bal et al., 2022). Stable appropriations also require group members to agree regarding technology use (Salisbury et al., 2002). Hence, appropriations are also indicated by consensus on appropriation. The intensity of *consensus* between the members of a group on how to appropriate the technology may differ from "high agreement to low agreement." Additionally, appropriations can also be defined in terms of attitudes towards use. These attitudes are constituted of beliefs concerning usefulness, ease of use, comfort, value, etc., offered by the technology.

In summary, appropriation reflects users' efforts to create their own sense of the technology (Mifsud et al., 2015), and can be theorised in terms of the dimensions listed in Fig. 1. A major lacuna of appropriation studies, thus far, has been a dearth of reliable and validated measurement scales for appropriation has been identified as a major lacuna of appropriation studies thus far (Loh and Chib, 2022). Majorly, appropriation of technological objects has been studied with the help of three distinct scales that capture the three global constructs encapsulated within AST-faithfulness of technology (Salisbury et al., 2002), consensus on appropriation (Chin et al., 1997), perceived ease of use and usefulness (F. Davis, 1989). Moreover, while these existing scales "seek to investigate (appropriation) within the context of group interaction, they fall short of capturing the range of adaptive behaviours available to individuals" (Schmitz et al., 2016, p. 681). Additionally, more recent definitions of appropriation have introduced some more important aspects like willingness to use technology (adoption), experimenting with technology uses (adaptation) and embedding it into everyday practices (integration) (Bal et al., 2022; Bar et al., 2016; Benamar et al., 2020). Considering the limited coverage of existing measures and their group-level focus, we aim to develop a GAIA scale that can holistically measure the construct at an individual level. Considering the limited coverage of existing measures, we aim to develop a GAIA scale that can holistically measure the construct. Based on this review, we've prepared a list of GAIA dimensions (Fig. 1) vis-à-vis technological appropriation at an individual level.

We now discuss some of the relevant drivers and outcomes of technological appropriation to establish the GAIA construct in its nomological network. To explain how an advanced information technology, such as GAI, is appropriated for work, we need to consider individual differences as well as contextual drivers (Charlier et al., 2016). The structure of the technology, as well as the task/organisation environment, has been delineated as important structural influences on technology appropriation (DeSanctis and Poole, 1994). The quality of a technology platform, task-relatedness, and empowerment climate have been empirically established as antecedents of ICT-enabled smart work appropriation by Ko et al. (2021). Leadership, as well, presents as a structural variable of importance, driving technology appropriation (Avolio et al., 2001; DeSanctis and Poole, 1994; Hussenot, 2008). Specifically, agile leadership (Joiner and Josephs, 2007), which is characterised by the ability to drive change and enhance creativity, has been discovered to impact technology appropriation. Agile leaders help create positive working environments that encourage employees to experiment, innovate and explore creatively (Fernandes et al., 2023). Additionally, given that the appropriation process is inherently creative (Bar et al., 2016; Lin et al., 2022), an individual's innovation orientation

Dimensions	Adjectives	(Barrett, 2018)	(Kang et al., 2012)	(Lin et al., 2022)	(Ylipulli et al., 2014)	(Benamar et al., 2020)	(Barrett, 2018)	(Salisbury et al., 2002)	(Chin et al., 1997)	(DeSanctis & Poole, 1994)	(Bal et al., 2022)	(Hussenot, 2008)	(Loh & Chib, 2022a)
Adopting	Technology acceptance, technology usage	✓			✓	✓					✓		
Adapting	Make it your own; explore new uses; experiment with technology; molding of technologies by giving meaning to them; user-defined technology use; alteration of intended usage	✓	✓	✓	✓	✓					✓	✓	✓
Integrating	Embed it into practices, integrating into everyday lives, social relationships and values; recontextualized adaptation.	✓			✓	✓					✓		
Attitudes towards use	Usefulness; ease of use; comfort; value							✓	✓	✓			
Consensus on approriation	degree of agreement among groups on usage		✓				✓	✓	✓	✓			
Faithfulness of appropriation	alignment with spirit of technology		✓				✓	✓	✓	✓			

Fig. 1. Dimensions of GAIA Source. Authors' own.

is considered significant in determining the adoption of new technologies. Those with a high innovation orientation are more open to trying out new technologies (Yi et al., 2006), and this orientation has been revealed to have an impact on the adoption and use of advanced technologies (Cimino et al., 2024). Consequently, high levels of innovation orientation lead to increased technology appropriation.

Vis-à-vis outcomes, it has been found that technology appropriation can positively influence task performance and job satisfaction (Ko et al., 2021). Technology appropriation has also been found to determine outcomes of self-perceived employability (Loh and Chib, 2019), psychological ownership and hubristic pride (Kirk et al., 2015). Existing research has also supported the idea that firms effectively utilising AI resources can enhance their creativity and performance (Mikalef and Gupta, 2021). Dwivedi et al. (2023) propose that Generative AI applications can combine different perspectives, stimulating creative thought processes among human agents. Therefore, the effective use of AI tools can improve individual creative performance (Mikalef and Gupta, 2021).

4. Methodology

To develop our GAIA scale, we have used a mixed-methods approach

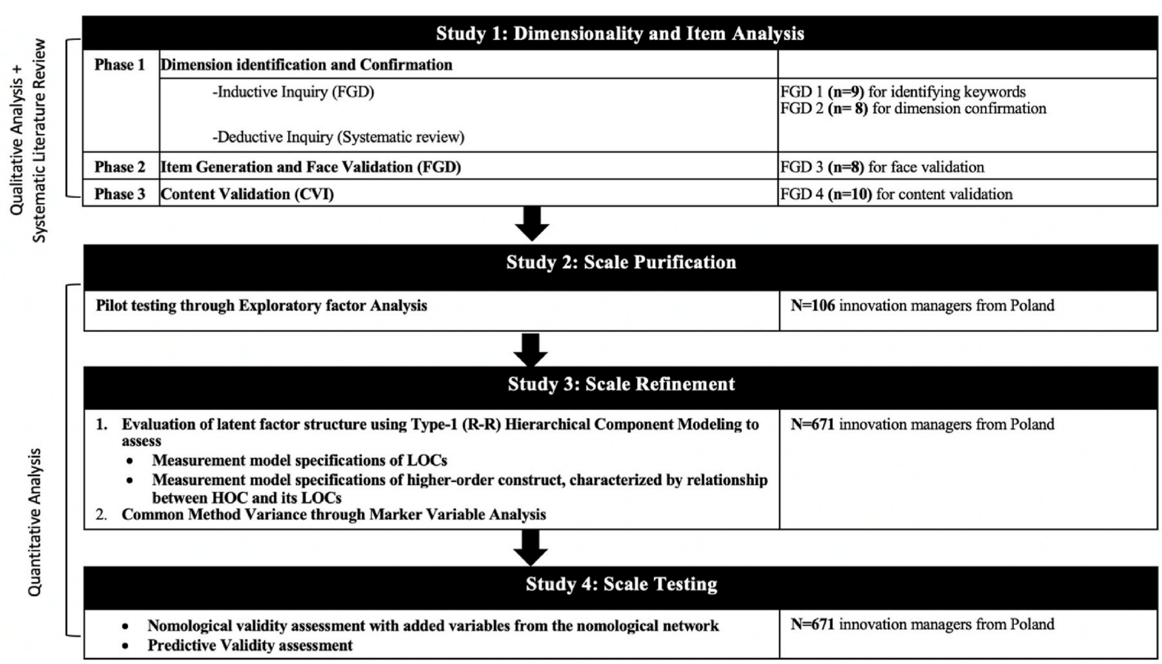

Fig. 2. Aspects and Statistics to Consider in Scale Development and Validation Process
Note: FGD= Focus Group Discussion; CVI= Content Validity Index; LOC = Lower order component; HOC= Higher order component.

wherein both qualitative and quantitative designs have been applied in combination. Combining insights from scale development methodologists over the years (Churchill, 1979; DeVellis, 2017; Finn and Kayandé, 1997; Hinkin, 1998; Netemeyer et al., 2003; Rossiter, 2002), we have conducted four studies (See Fig. 2) to conceptualise, construct and validate the GAIA scale.

Partial least squares-structural equation modeling (PLS-SEM) has been used to this end. According to Dash and Paul (2021), the choice of method should align with the study objectives, and for theory development purposes like ours, PLS-SEM is a more suitable approach. PLS-SEM models the constructs as composites, serving as valid proxies for the conceptual variables being examined (Hair et al., 2021). Further, the constraint of fit requirements in CB-SEM results in the elimination of a greater number of indicators than in PLS-SEM. These deleted indicators often contain meaningful content and face validity, and lead to loss of content (Astrachan et al., 2014). The loss of content at theory development is a difficult tradeoff to accept, and maximising retention of measures, even at the cost of model fit, if needed, is recommended (DeVellis, 2017). To avoid this loss of content and enhance the reliability and validity of the scale, PLS-SEM has been used as a more gentle item-purification method in the beginning. However, considering the importance of establishing a good fitting model, this study simultaneously aims to minimise the tradeoff between item retention and model fit. Thus, CB-SEM has been employed for the assessment of this dimensional structure using global model fit criteria.

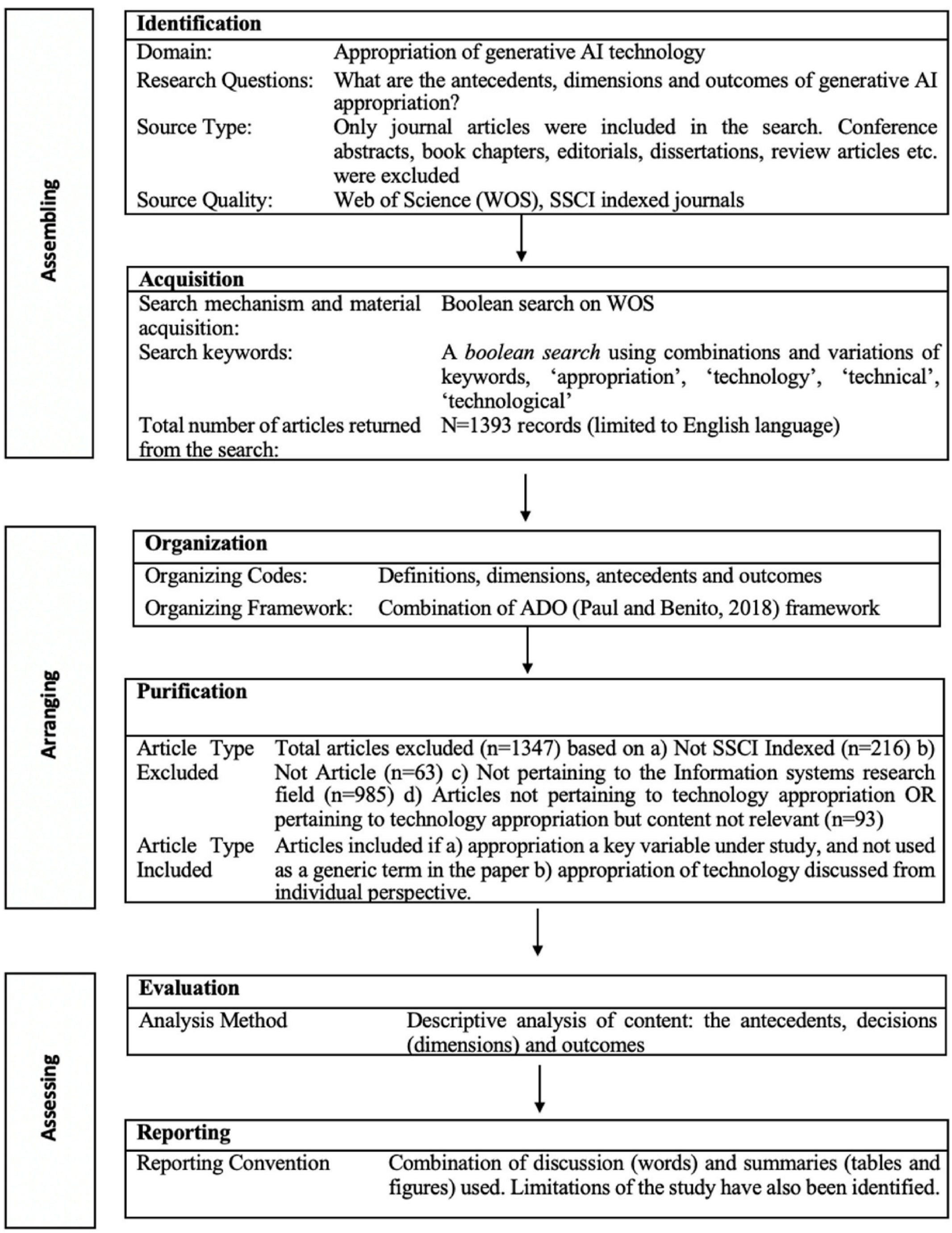

Fig. 3. SPAR-4-SLR review protocol (Paul et al., 2021) for GAIA Source: Author's Own.

4.1. Procedures

The development and validation of the GAIA scale is a culmination of four in-depth studies elucidated in Fig. 2. Primarily, the process starts with an analysis of dimensionality and items. This is followed by an exploratory factor analysis for scale purification and an evaluation of latent factor structure using hierarchical component modeling for scale refinement. Study 4 is characterised by assessment of predictive strength and nomological validation. A discussion on sampling details and methods used in each of these studies ensues in the following sections.

5. Scale development

5.1. Study 1: dimensionality and Item analysis

This study was aimed at generating a validated item pool to measure GAIA using inductive and deductive methodologies.

5.1.1. Dimension identification and dimension confirmation

To identify the empirical attributes that can represent the GAIA construct aptly, we first conducted an FGD, aimed at identifying keywords and ensuring that aspects relevant to the current landscape were incorporated. It was conducted in April 2023 and consisted of one researcher each from Poland, Italy, and India, and two innovation managers from the aforementioned countries (n = 9).

Following this, we conducted a systematic review of technological appropriation literature. We adopted Paul et al.'s (2021) highly rigorous SPAR-4-SLR approach to methodically and concisely summarise the extant literature (Paul et al., 2021). This approach incorporates three stages, i.e., assembling, arranging, and assessing, which are further divided into six distinct sections: identification, acquisition, organisation, purification, evaluation, and reporting. The protocol, with accompanying details regarding source type, source quality, keywords and inclusion/exclusion criteria, has been summarised in Fig. 3. After a thorough analysis, 46 full-text articles were selected for this study. We analysed studies addressing the antecedents, dimensions, and outcomes in GAIA research. This part of phase one was completed in May 2023.

A second FGD was also conducted to ensure all pertinent dimensions had been incorporated in the dimension table. A group of 8 experts comprising three researchers (one from each country), three innovation managers and two research methodology experts was constituted, who then vetted the dimensions given in Fig. 1. It was recommended that the dimension corresponding to integration be divided into two-integration into work practices and integration into organisational culture. It was also recommended that consensus on appropriation be dropped since it is a global/institutional level variable that is not applicable when studying appropriation at the individual level.

5.1.2. Item generation and face validation

Once the dimensions were confirmed, the next objective was to generate items pertaining to GAIA, and then to select those items that have face validity. An initial pool of 53 items was developed. A third FGD was convened at this stage to establish face validity. Wording clarity, redundancy and response formats were some of the aspects taken into consideration here (Netemeyer et al., 2003; Papadas et al., 2017). The 8-member focus group comprised 3 researchers, 3 innovation managers and 2 research methodology experts with specialisation in the area of scale development. 9 items were dropped at this stage, and 2 were added. 5 items were modified for clarity. 46 face validated items were then assessed for content validity.

5.1.3. Content validity using content validity index (CVI)

Content validity audits the extent to which an instrument possesses sample items that aptly pertain to the construct under assessment (Polit and Beck, 2006; Rossiter, 2002). To establish the content validity of our scale, we have drawn on the most widely accepted measure of content validity- CVI (Kovacic, 2018; Lynn, 1986). The systematic six-step process detailed by Yusoff (2019) has been followed for CVI calculation. First, a content validation form was prepared to provide the experts with an absolute understanding of the task and accompanying expectations (Yusoff, 2019). An instruction set by which experts can adjudge the content relevance of items was also shared. A definition of the construct was provided to them to enable consistency in the scoring process. For scoring, a 4-point scale suggested by Polit and Beck (2006), wherein 4 = highly relevant, and 1 = not relevant, was used. Secondly, following the recommendations of Polit et al. (2007), a panel of 10 content experts was sought for assessing content validity. Expert selection criteria were representative of a) scale development methodologists in general, or b) subject matter experts in the area of technology adoption, technology acceptance and/or technological determinism. In the next step, an expert panel focus group meeting was convened to conduct the content validation. Each of the experts (labelled E1-E10) was asked to rate the relevance of each item to the underlying construct using the content validation form. Fourth, the sample of experts independently scored each item on the scale. Experts were asked to review the scale items and score them by paying heed to the domain definition shared in the form. Fifth, once all items had been scored independently, experts submitted their forms to the researchers. Finally, calculations were made. Two types of CVI have been computed in this study- I-CVI, which ascertains content validity at the individual item level, and S-CVI, which pertains to the overall scale (Polit et al., 2007). Before beginning the computations, the recorded relevance ratings of 3 or 4 were coded as 1, and those of 2 or 1 were coded as 0 (Almanasreh et al., 2019).

5.1.3.1. I-CVI: The values for I-CVI for each item on the scale were calculated by dividing the number of experts in agreement by the total number of experts (Davis, 1992; Polit and Beck, 2006; Yusoff, 2019). *Experts in Agreement (A)* are calculated by summing relevance ratings provided by the N = 10 experts for each item. *Universal Agreement (UA)* is calculated by assigning items a rating of 1 or 0. Items where all experts have assigned a relevance rating of 3 or 4 are assigned a 1, while items with even one expert who is not in agreement are assigned a rating of 0. According to guidelines by Lynn (1986), for more than 9 experts, I-CVI values of 0.78 and above are acceptable.

5.1.3.1. Modified Kappa (κ): to adjust for chance agreement amongst the panel of experts, a κ* statistic was also computed (Polit et al., 2007), using the formula*

$$\kappa^* = \frac{ICVI - P_c}{I - P_c} \tag{1}$$

where P_c is the chance probability and is calculated as under

$$P_{c=}\ (N!\,/\,A!(N-A)!)^*0.5^N \tag{2}$$

Only those items that had I-CVI $\geq$0.78 and $\kappa^* > 0.75$ were retained. The final instrument at this stage consisted of 37 items, all of which had been rated as excellent.

5.1.3.3. S-CVI: Further, the overall content validity of the scale was determined using S-CVI/Ave, which is calculated by averaging the scores of I-CVI for all items. S-CVI/Ave equalled 0.911 (=33.7/37; wherein 33.7 is the summation of all I-CVIs, and 37 is the total number of items). This value is greater than the minimum threshold of 0.90 (Almanasreh et al., 2019; Waltz et al., 2010), establishing the overall validity of our scale.

These 37 items (with I-CVI$\geq$ 0.78, κ^*> 0.75, and S-CVI/Ave$\geq$ 0.9) were then pilot-tested.

5.2. Study 2: scale purification

In this study, the preliminary 37-item scale was pilot tested. A self-administered questionnaire with seven-point scaling (with 1 = strongly disagree and 7 = strongly agree) was used to collect data from respondents. Data was collected from 106 innovation managers in Poland using snowball sampling. The sample profile was representative of the population. The sample size was determined using the subject-to-item ratio, following best practices (Costello and Osborne, 2005). The subject-to-item ratio was calculated to be approximately 2.9:1, which exceeds the critical threshold of 2.5:1.

Prior to factor extraction, sample suitability for conducting exploratory factor analysis was determined, wherein factorability of the data was assessed using Keiser-Meyer-Olkin (KMO) test (Kaiser and Rice, 1974) and Bartlett's Test of Sphericity (Bartlett, 1950). KMO test returned a value of 0.899 (>0.6required to establish sampling adequacy). Bartlett's test of sphericity (2473.84, df. 406, $p < 0.001$) shows that the values are significant and hence, acceptable for continuing with factor analysis (Field, 2013; Hair et al., 2010).

Next, to empirically establish the dimensionality of the GAIA scale, we conducted a principal components analysis using varimax rotation with Kaiser normalisation (SPSS 24.0) on the 37 items retained in the final phase of Study 1. As a rule of thumb, items with factor loadings <0.5 and communalities <0.5 were dropped. Items that cross-loaded onto two or more factors were also removed. Additionally, items that loaded onto factors with an eigenvalue <1 were deleted (Kaiser and Rice, 1974). This yielded a 29-item, five-factor solution for GAIA after 7 iterations (See Table 1), explaining 70.414 % of variance. This is greater than the prescribed threshold of at least 60 % (Hair et al., 2010). The overall reliability of the GAIA scale is 0.91, which is greater than the cut-off value of 0.7 (Nunnally and Bernstein, 1978). Good internal consistency of individual dimensions was observed (Table 1). The emerging five factors have been labelled a) Integrative Appropriation, b) Adoptive Appropriation, c) Customised Appropriation, d) Interface Appropriation, and e) Ethical Appropriation.

5.3. Study 3: scale refinement

This study focused on scale refinement. Data was collected via a commercial Polish agency, wherein innovation managers across six industries were selected. Innovation managers were identified as professionals who were responsible for the implementation of changes to improve a company's productivity and efficiency at any stage of the business process. 15579 applications were sent through simple random sampling, out of which only those responses were retained where respondents indicated that they use Generative AI. The final sample comprised 671 useable responses. When the data was collected during

Table 1
Exploratory factor analysis (EFA).

Components→ Item↓	Integrative Appropriation	Adoptive Appropriation	Customized Appropriation	Interface Appropriation	Ethical Appropriation
I rely on Generative AI as a valuable resource to expand my knowledge.	0.773				
Generative AI helps me develop problem-solving skills	0.732				
Generative AI helps me enhance the quality of my work reports.	0.702				
Generative AI enhances my decision-making process by providing valuable insights.	0.653				
Generative AI helps me to finish my work quickly	0.637				
I feel confident that Generative AI aligns with our organization's goals.	0.628				
Generative AI is my personal assistant for brainstorming	0.626				
I find Generative AI useful in generating creative ideas or content.	0.593				
I trust the reliability of the responses generated by Generative AI.	0.584				
I find Generative AI a good tool for work	0.558				
I'm interested in using Generative AI functions		0.822			
I'm willing to use Generative AI functions		0.819			
Using Generative AI improves my effectiveness		0.742			
I consider Generative AI as a valuable tool that contributes to the overall success of my work.		0.674			
I can validate my thought process through Generative AI		0.623			
Using Generative AI allows me to help solve many queries		0.596			
I have modified Generative AI to leverage its potential			0.815		
I can't wait to invent new uses of Generative AI			0.758		
I proactively seek updates to ensure optimal usage of Generative AI.			0.745		
I feel in control over Generative AI functions			0.652		
I feel comfortable experimenting with different settings of Generative AI.			0.609		
I've modified my everyday work practices to leverage the possibilities of Generative AI			0.603		
I am invested in exploring new capabilities of Generative AI to help me complete my work tasks			0.563		
I find Generative AI user-friendly				0.787	
Generative AI interface is very smooth				0.746	
I think Generative AI can be used in multiple ways constructively				0.678	
I think it is okay to use technology to suit to your benefit					0.904
I think it is okay to improperly use Generative AI if it suits the organization					0.622
I think it is okay to use Generative AI even beyond its general intent					0.586
Eigen Value	*13.814*	*2.151*	*1.706*	*1.398*	*1.351*
Cronbach's α	*0.91*	*0.92*	*0.90*	*0.86*	*0.84*
Total Variance Explained	*70.414 %*				

June–July 2023, this was the time GAI was gaining impetus. The most commonly used application of GAI at the time was ChatGPT, so much so that it was almost generic in understanding the GAI construct. As of June 2023, ChatGPT accounted for more than 60 % of market share in terms of web traffic to the top 50 most-used Generative AI products as well as subscription sales of AI tools (Andreessen, 2023; Backlinko, 2024; Earnest Analytics, 2024). Consequently, data was collected from innovation managers with reference to ChatGPT as an example case.

5.3.1. Evaluation of latent factor structure

A confirmatory factor analysis (CFA) was further conducted to evaluate model fit and confirm the dimensionality of the GAIA scale. Latent factor structure was validated using PLS-SEM in SMARTPLS 4.0. Hierarchical Component Modeling (Jarvis et al., 2003) using the disjoint two-stage approach (Becker et al., 2023) was used to establish the relationship between the construct and its indicators.

GAIA was conceptualised as a Type 1 HCM, with reflective first-order, reflective-second-order. Type 1 reflective-reflective hierarchical latent variable models are most appropriate when the study objective is to find the common factor of several related, yet distinct reflective constructs (Jarvis et al., 2003). In the study, the higher-order construct GAIA represents a more general or abstract construct that simultaneously explains all the underlying LOCs. In other words, GAIA can be represented by a number of more concrete aspects, measured by LOCs that capture specific attributes of GAI appropriation like integrative appropriation, adoptive appropriation, customised appropriation, interface appropriation and ethical appropriation. Two things deserve mention here. One, these LOCs are highly correlated, often with overlapping perspectives. Consider, for example, Integrative and Customised appropriation. Customised appropriation constitutes the extent to which a user adapts/reconfigures/reinvents a technology in the process of making it their own (Hussenot, 2008; Ylipulli et al., 2014), while integrative appropriation can be understood as the embedding of technology in everyday lives (Mifsud et al., 2015). This is to say that, in an attempt to derive maximum utility from any technology, when various users negotiate with GAI, they may invent practices around its myriad possibilities. Now, in the process of tailoring GAI to their ends (which is customised appropriation), users may very often end up embedding GAI in their everyday practices (integrative appropriation). Gaskin and Lyytinen (2012) liken appropriation to taking psychological ownership of technology, wherein users select "which features of a technology to use and how to use them – effectively taking responsibility for the way a technology is used". The selected use of the technology is then integrated into work practices. Thus, these two dimensions of GAI, customised and integrative appropriation, are correlated. Two, despite the correlation, Generative AI appropriation can be expressed in different ways here. For instance, even if one does not find the GAI interface smooth (interface appropriation), they may be interested in using GAI functions (adoptive appropriation), and hence, it will still be termed as Generative AI appropriation. As such, these LOCs are distinguishable from each other. From these two instances, it is evident that these lower-order constructs are distinguishable from each other, and yet correlated, and hence best modelled as a Type 1 reflective-reflective construct (Becker et al., 2012).

Further, implementing higher-order constructs involves examination of (1) measurement model specifications of LOCs, and (2) measurement model specifications of higher-order constructs, characterised by the relationship between HOC and its LOCs (Sarstedt et al., 2019; Wetzels et al., 2009). Accordingly, we will evaluate the measurement properties of the latent factor structure for LOCs and the higher-order construct as a whole.

5.3.1.1. Measurement model specifications of LOCs. To evaluate the measurement properties of the reflective-reflective higher-order index, we examined indicator reliability, internal consistency reliability, convergent validity and discriminant validity. To establish indicator reliability, we analysed the outer loadings (Table 2). As a rule of thumb, loadings $\geq$0.708 are considered acceptable (Hair et al., 2019), which is the case for the majority of items retained. However, in social sciences studies, especially with development of new scales, indicators with loadings between 0.4 and 0.7 should only be considered for deletion under two conditions (Hair et al., 2021): one, when their respective internal consistency reliability and convergent validity values fall below threshold levels, and two, when their deletion doesn't impede content validity. Internal consistency reliability was assessed using Cronbach's α, composite reliability (ρ_c), and reliability coefficient (ρ_a). The values for these criteria fall within the acceptable threshold of 0.7–0.95 (Hair et al., 2021). To establish convergent validity of the construct, we have examined the criterion, average variance extracted (AVE), for our five LOCs and found them well above the threshold of 0.5 (Refer to Table 2).

Finally, discriminant validity at the item-level has been ascertained by examining the independence of item loadings (Voorhees et al., 2016), i.e., the cross-loading matrix. It can be observed that each item correlates most strongly with the LOC to which it is theoretically associated, and that, loading of an item on related LOC is greater than any cross-loadings on other LOCs. Thus, discriminant validity of the construct at the item level has been established (Gefen and Straub, 2005).

5.3.1.2. Measurement model specifications of HOCs. For further assessment of the second-order factor structure, we performed a Type I reflective-reflective, second-order CFA by loading the five LOCs onto the HOC. Factor loadings ranged between 0.82 and 0.93 (refer to Table 3). Values of Cronbach's α, ρc and ρa were found to be above 0.7 (Bagozzi and Yi, 1988; Sarstedt et al., 2021). AVE value for the overall GAIA construct is 0.81. The discriminant validity of first-order components was assessed using the HTMT ratio of correlations. All values were well within the range (<0.9) (Gold et al., 2001), demonstrating adequate discriminant validity of all the latent variables. However, the HTMT ratio is over 0.90 between integrative appropriation and adoptive appropriation as well as between integrative appropriation and customised appropriation, but it lies between the lower and upper bounds of the 95 % confidence intervals when tested at 10,000 bootstrapping subsamples (Hair et al., 2021). Pursuant to the HTMT inference approach, an HTMT ratio of 1 is acceptable (Hair et al., 2021; Shiva et al., 2023). In this context, the confidence interval method is deemed to be a suitable approach via 10,000 bootstraps. Thus, the discriminant validity of the GAIA scale is supported. As for integrative appropriation with adoptive appropriation, the HTMT ratio is 0.906, which is well within the lower and upper bounds of the confidence interval, i.e, 0.876 and 0.932, respectively. Similarly, for integrative appropriation and customised appropriation, the HTMT ratio is observed at 0.948, which is between the lower and upper bounds of 0.924 and 0.970, respectively. Table 4 enlists the discriminant validity of the proposed scale (Shiva et al., 2023). Moreover, the obtained CFA results suggested adequate model fit with acceptable fit indices (SRMR = 0.049).

5.3.1.3. Global model fit indices. In order to assess the dimensional structure of the scale using global model fit criteria, CB-SEM was also used. Primarily, confirmatory factor analysis (CFA) was performed in order to confirm the factor structure of the GAIA scale and to establish convergent and discriminant validity. All the results were found to be in place. Indicator loadings were found to be greater than 0.7 (Hair et al., 2010) for both first and second order. Indicator loadings were found to be higher in PLS-SEM compared to CB-SEM, as has also been observed in previous studies (Dash and Paul, 2021). Internal consistency reliability of the scale was established using Cronbach's α and composite reliability (ρ_c), with all values falling within the acceptable threshold of 0.7–0.95 (Hair et al., 2021). AVE values were found to range between 0.60 and 0.78 (well above the threshold of 0.5). CB-SEM additionally provides

Table 2
Measurement model summary for LOCs (n = 671).

LOC	Identifier	Indicator	Indicator Reliability (Loadings)		Cronbach's α	rho_c		Convergent Validity (AVE)	
			PLS SEM	CB SEM		PLS SEM	CB SEM	PLS SEM	CB SEM
IA					*0.91*	*0.94*	*0.92*	*0.79*	*0.73*
	GAIA_IA_2	Generative AI helps me develop problem-solving skills	0.90	0.88					
	GAIA_IA_5	Generative AI helps me to finish my work quickly	0.91	0.88					
	GAIA_IA_6	I feel confident that Generative AI aligns with our organization's goals.	0.90	0.86					
	GAIA_IA_9	I trust the reliability of the responses generated by Generative AI.	0.85	0.79					
AA					*0.91*	*0.94*	*0.91*	*0.85*	*0.78*
	GAIA_AA_1	I'm interested in using Generative AI functions	0.93	0.90					
	GAIA_AA_2	I'm willing to use Generative AI functions	0.94	0.91					
	GAIA_AA_5	I can validate my thought process through Generative AI	0.90	0.85					
CUA					*0.92*	*0.94*	*0.92*	*0.71*	*0.66*
	GAIA_CUA_1	I have modified Generative AI to leverage its potential	0.83	0.76					
	GAIA_CUA_2	I can't wait to invent new uses of Generative AI	0.82	0.78					
	GAIA_CUA_3	I proactively seek updates to ensure optimal usage of Generative AI.	0.88	0.85					
	GAIA_CUA_4	I feel in control over Generative AI functions	0.83	0.79					
	GAIA_CUA_5	I feel comfortable experimenting with different settings of Generative AI.	0.86	0.84					
	GAIA_CUA_6	I've modified my everyday work practices to leverage the possibilities of Generative AI	0.86	0.83					
IFA					*0.85*	*0.91*	*0.85*	*0.77*	*0.65*
	GAIA_IFA_1	I find Generative AI user-friendly	0.90	0.88					
	GAIA_IFA_2	Generative AI interface is very smooth "	0.85	0.74					
	GAIA_IFA_3	I think Generative AI can be used in multiple ways constructively	0.88	0.80					
EA					*0.82*	*0.90*	*0.82*	*0.73*	*0.60*
	GAIA_EA_1	I think it is okay to use technology to suit to your benefit	0.83	0.74					
	GAIA_EA_2	I think it is okay to improperly use Generative AI if it suits the organization	0.85	0.79					
	GAIA_EA_3	I think it is okay to use Generative AI even beyond its general intent	0.89	0.80					

Note:LOC = Lower order component; AVE = Average variance extracted; Integrative Appropriation = IA; Adoptive Appropriation = AA; Customized Appropriation = CUA; Interface Appropriation = IFA; Ethical Appropriation = EA; Cronbach's alpha = α; Reliability Coefficient = ρ_a; Composite reliability = ρ_c.

Table 3
Measurement model Summary for HOCs.

HOC	Reflective Indicators	Indicator Reliability	Internal Consistency Reliability			Convergent Validity
		Loadings	α	ρ_a	ρ_c	*AVE*
GAIA			*0.94*	*0.95*	*0.95*	*0.81*
	IA	0.93				
	AA	0.91				
	CUA	0.93				
	IFA	0.90				
	EA	0.82				

Note: HOC=Higher order component; AVE = Average variance extracted; GAIA = Generative AI Appropriation; Integrative Appropriation = IA; Adoptive Appropriation = AA; Customized Appropriation = CUA; Interface Appropriation = IFA; Ethical Appropriation = EA; Cronbach's alpha = α; Reliability Coefficient = ρ_a; Composite reliability = ρ_c.

model-fit indices, which were examined to validate the scale (See Table 5). All these indices were found to be within the acceptable range.

Additionally, we also compared our estimated model against multiple alternate factor models. Across all comparisons, the estimated five-factor model consistently exhibited superior fit indices, indicating a better overall model fit.

5.3.2. Common method variance (CMV)

CMV is the variance arising from measurement method errors (Podsakoff et al., 2003). To address CMV, we used a marker variable (Lindell and Whitney, 2001; Podsakoff et al., 2012), fashion

Table 4
Discriminant validity.

HTMT Correlations	HTMT	Confidence Intervals	
		2.50 %	97.50 %
Customised Appropriation <–> Adoptive Appropriation	0.854	0.820	0.886
Ethical Appropriation <–> Adoptive Appropriation	0.791	0.730	0.844
Ethical Appropriation <–> Customised Appropriation	0.834	0.770	0.889
Integrative Appropriation <–> Adoptive Appropriation	0.906	0.876	0.932
Integrative Appropriation <–> Customised Appropriation	0.948	0.924	0.970
Integrative Appropriation <–> Ethical appropriation	0.847	0.785	0.898
Interface Appropriation <–> Adoptive Appropriation	0.888	0.847	0.926
Interface Appropriation <–> Customised Appropriation	0.860	0.819	0.898
Interface Appropriation <–> Ethical Appropriation	0.782	0.718	0.843
Interface Appropriation <–> Integrative Appropriation	0.860	0.819	0.896

consciousness (Simmering et al., 2015), which is a theoretically unrelated variable to other constructs in the study. It was measured using the item "I would say I am very fashion conscious". The difference between R^2 values before and after adding the MV was within the prescribed range of 10 per cent (Ahmad et al., 2020). The relationship between MV

Table 5
Model fit indices.

Fit Indices	Estimated Value	Threshold Value
SRMR	0.051	<0.08 (Jarvis et al., 2003)
NFI	0.902	>0.90 (Dash and Paul, 2021)
TLI	0.901	>0.90 (Dash and Paul, 2021)
CFI	0.913	>0.90 (Hu and Bentler, 1999)
RMSEA	0.096	<0.1 (Browne and Cudeck, 1992; Heblich et al., 2023)

and GAIA was found to be insignificant ($\beta = 0.027$, $p = 0.19$). Hence, CMV is not a potential cause for concern.

5.3.3. Tetrad analysis

We also conducted a confirmatory tetrad analysis (CTA-PLS) to test our model specifications (Hair et al., 2019). Tetrads, i.e., differences between pairs of covariances among indicators, were analysed to confirm the formative or reflective nature of the construct. The confidence intervals of the resulting tetrads included zero value, and hence were found to be non-significant for our study (Bollen and Ting, 2000; Noor et al., 2022), establishing GAIA as a reflective construct with empirical support.

5.4. Study 4: scale testing

Study 4 involves scale testing by embedding the construct within a theoretical framework to evaluate its nomological validity and predictive strength (Lim, 2024).

5.4.1. Nomological validity

According to Kock et al. (2024), the quality of a scale depends on the nomological network in which it is tested and placed. The nomological network used to evaluate the nomological validity of GAIA consisted of three constructs identified in the literature (ADO framework, Section 3) and finalised by the expert focus group. Thus, Agile Leadership (Avolio et al., 2001; Cimino et al., 2024), Innovation Orientation (Yi et al., 2006; Thomas et al., 2024b), and Individual Creative Performance (Mikalef and Gupta, 2021) formed the nomological network of appropriation. The paths from Agile leadership to appropriation ($\beta = 0.144$; $p < 0.05$) and innovation orientation to appropriation ($\beta > 0.415$; $p < 0.05$) were found to be significant. The R^2 value was also determined for appropriation and found to be 0.249, indicating that agile leadership and innovation orientation explain 24.9 % of the variance in appropriation. These findings were extended with a testing for predictive validity which evaluates the extent to which GAIA can forecast an outcome grounded in prior literature, Individual Creative Performance (ICP).

5.4.2. Predictive validity

The causative relationship between GAIA and ICP was taken as a reference frame for examining the predictive validity of the proposed scale. To investigate this relationship, we adopted the 13-item scale for ICP given by Zhou and George (2001). As per the nomological network established by existing literature, effectively utilising AI tools can improve creativity and performance (Mikalef and Gupta, 2021). Evolving business dynamics have placed the creative performance of employees as an important factor for organisational success (Mutonyi et al., 2020). Human-computer interaction shows promise for enhancing an individual's creative performance (Li et al., 2022). According to Grech et al. (2023), generative AI can be used to expand human creativity by providing assistance in work processes, such as brainstorming, critical thinking and problem solving. In this vein, Dwivedi et al. (2023) have suggested empirically analysing this relationship. Based on this, we propose a causal relationship between GAIA and ICP.

H1. GAIA has a positive and significant effect on ICP.

The effect of GAIA on ICP was found to be positive and significant ($\beta = 0.35$, $p < 0.001$), indicating that high levels of GAIA positively influence the ICP of employees (Refer to Fig. 4). This finding is also supported by extant literature that theorises the causal impact of the relationship between generative AI technologies on creative performance (Dwivedi et al., 2023; Grech et al., 2023). By empirically establishing the causal link between GAIA and ICP at a micro-level situated within the organisational context, our scale, thus, demonstrates predictive validity.

6. Discussion

In this study, we have conceptualised and developed a validated scale to measure GAIA. Empirical examination establishes GAIA as a second-order, reflective-reflective construct with 19 items and 5 dimensions. The scale demonstrates acceptable levels of content validity, reliability, convergent validity, discriminant validity and nomological validity. Study findings suggest that managerial employees perceive GAIA as a function of integrative, adoptive, customised, interface and ethical appropriation.

6.1. Dimensional structure of GAIA

Integrative appropriation reflects the level to which Generative AI has been embedded into work practices. Appropriation constitutes an ongoing iterative process whereby users interact with a technology. Existing research equivocally suggests that appropriation cannot occur until a user masters a technology, feels comfortable with it, and sufficiently manages it (Benamar et al., 2020). It is through appropriation that individuals transform "technology as designed" to "technology as used" (Carroll et al., 2003). People are active participants in the shaping of a technology, and they do this by integrating the technology into their daily practices and social relationships (Benamar et al., 2020). Conceptualised as a behaviour in information systems research, appropriation has been categorically understood in terms of the "way users integrate a technical tool into their organisational routines" (Mifsud et al., 2015). In consonance with scholarship centring around "the situated use of technology", this particular dimension captures the creative renegotiation process on the part of the employees through which they integrate Generative AI into everyday work tasks like problem-solving, decision-making, time management and brainstorming (Bar et al., 2016). Thus, this factor, as a reflection of employees' trust in the ability of Generative AI to improve the quality of their work products achieved through integration, constitutes a characteristic appropriation behaviour that determines continued usage.

The second factor, *adoptive appropriation*, represents the extent to which users have accepted Generative AI and are willing to use it in their lives. Technology appropriation, in the most basic sense, has been delineated as "user-defined technology use" (Lin et al., 2022). At the core of this concept is the notion of affordance, which entails that individuals make use of technological tools in their surrounding context to achieve a purpose (Bar et al., 2016). According to Ko et al. (2021), appropriation occurs when users use technologies in order to achieve work outcomes. Therefore, the interest in, and intention to use a technology like Generative AI, is thus an elemental step to understanding how appropriation materialises. This dimension signifies users' perception regarding Generative AI use in work-related activities, and hence captures an important appropriation attribute (Benamar et al., 2020; Carroll et al., 2003).

Customised appropriation, the third factor in GAIA's dimensional structure, can be understood as the extent to which a user adapts a technology, effectively making it their own in the process. Kirk et al. (2015, p.166) define technology appropriation as "the customisation and idiosyncratic use of technology". Customising the technology to suit one's needs is an essential facet of appropriation, one that distinguishes appropriation from adoption (Hussenot, 2008; Loh and Chib, 2022;

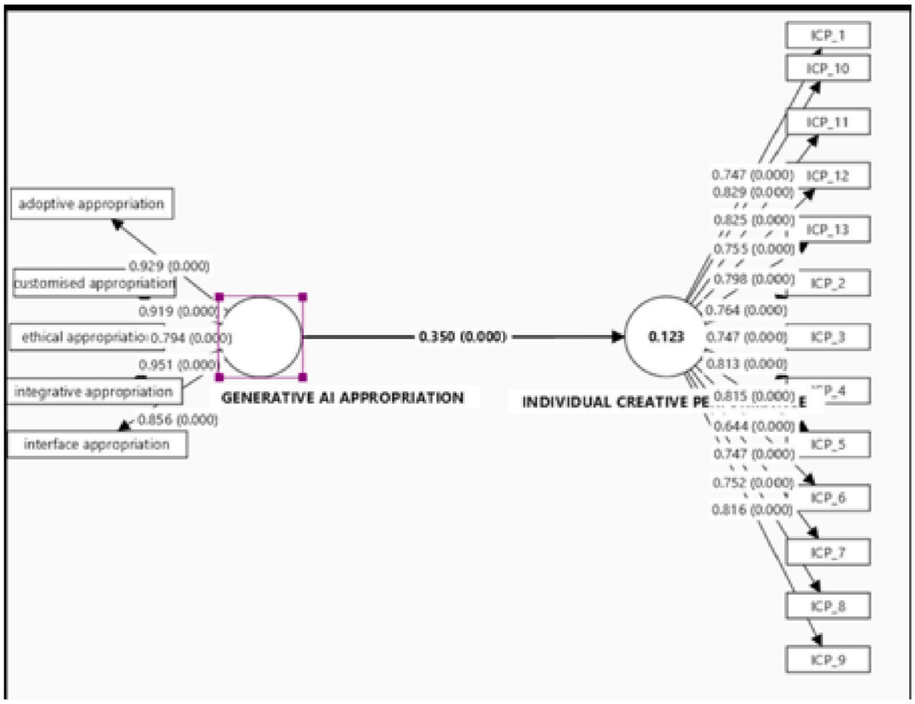

Fig. 4. Results of predictive validity testing.

Ylipulli et al., 2014). Users are active participants in shaping of the technology and often reconfigure the technology to suit their local needs (Bal et al., 2022; Benamar et al., 2020). According to Orlikowski (2000, p. 408) "when users choose to use a technology, they are also choosing how to interact with that technology." These users pick and choose among different elements of a technology, utilising and appropriating certain aspects of a technology product or service, while neglecting, rejecting or even disappropriating others (Kirk et al., 2015). Loh and Chib (2022) refer to this appropriation phenomenon as "recontextualised adaptation". Hence, this dimension encapsulates an important facet of GAIA, i.e., the proclivity towards experimenting with Generative AI functions in order to explore the repertoire of its capabilities and leverage the wealth of its possibilities.

Interface appropriation, the fourth factor, delineates the user's attitude towards Generative AI use. Favourable attitudinal dispositions towards a technology constitute an important indicator of appropriation (Desanctis and Poole, 1994; Salisbury et al., 2002), considering that technology appropriation is often referred to as "user-defined technology use" (Lin et al., 2022). Users engage and interact with a technology, its applications, features and peripherals to control their technology experience (Kirk et al., 2015). This experience of interaction is essential to the appropriation of a technology, as appropriation requires emotional and cognitive engagement (Loh and Chib, 2022). Since users always test and negotiate with a technology before adopting it, a positive attitude toward Generative AI may help develop a connection with GAI, enabling its appropriation. Hence, factors like perceived ease of use and perceived usefulness of a technology become key indicators of its appropriation. Inherently, this dimension captures users' ease with using the platform, as well as the degree to which they find it useful, forming an elemental dimension of GAI appropriation.

The final factor, *ethical appropriation*, is a measure of one's ethical disposition towards Generative AI use. An important concept within the extant appropriation literature has been that of faithful appropriation, or alignment with the spirit of the technology (Chin et al., 1997; Desanctis and Poole, 1994; Kang et al., 2012). However, more recent research has emphasised that unfaithful (or ironic) appropriation may not always be improper or negative, but rather just not in line with the original intent of the technology (Barrett, 2018). Therefore, an altered perspective on 'spirit of the technology' is essential to map the concept of appropriation from group-level to individual-level. In this regard, Schmitz et al. (2016, p. 668) posit that "the spirit of a technology introduced as the designer's intent must be reconceptualised in this era of malleable technology where the user participates in the (re)design of technology structures". The nature of modern technologies is so versatile and flexible that they can be leveraged beyond their original purposes, motivating employees to introduce innovative functionalities aligned with their current work practices (Bal et al., 2022). This brings into question the notion of only faithful appropriations as an indicator of appropriation. The proposed scale challenges this, bringing even ironic appropriations under the umbrella of appropriations, and instead presents the idea of an ethical appropriation, focused on an alignment with moral codes of conduct, rather than intended functionalities. This dimension captures this ethical disposition of the user, i.e., if the user is willing to appropriate beyond the faithful appropriation for innovation.

The derived empirical factor structure largely resembles the theoretically conceptualised structure, deviating only at two instances (refer to Table 6 for details). The first two empirical dimensions, "Integrative Appropriation" and "Adoptive Appropriation", correspond to the integrating and adopting theoretical enumerations of the construct. The third dimension, Customised Appropriation, corresponding to the adapting dimension from literature, only reflects a labelling difference. The Interface Appropriation dimension is where the first point of deviation arises. The dimension finds its theoretical base in the literature dimension of attitude towards use, which comprises beliefs concerning usefulness, ease of use, comfort, value, etc., offered by the technology. The empirical dimension, however, only captures the interface-related aspects, as is evident from the constituting statements, and hence the dimension has been named as such. The final theoretical dimension of faithful appropriation assesses alignment with the spirit of technology. However, recent literature suggests that innovative uses result from ironic appropriations, i.e., using technology in a way that is inconsistent with how it ought to be used (Bal et al., 2022; Barrett, 2018). The final dimension of ethical appropriation is a refinement of the concept of faithful appropriation, bringing even ironic appropriations of a technology under the umbrella of appropriations, and instead focusing on the ethical or unethical intent behind using the technology. This

Table 6
Mapping the theoretical conceptualisation with empirical factor structure.

Theoretical Conceptualisation		Empirical Factor Structure	
Integrating	Defined in terms of embedding into everyday lives.	**Integrative Appropriation**	The extent to which Generative AI has been embedded into everyday work tasks like problem-solving, decision-making, time management and brainstorming
Adopting	Constitutes the decision of choosing to use a particular technology, and can be understood as an individual's interest in, and willingness to use Generative AI.	**Adoptive Appropriation**	The extent to which users have accepted Generative AI and are willing to use it in their lives
Adapting	Customisation and idiosyncratic use of technology; the extent to which an innovation is changed during its adoption and implementation	**Customised Appropriation**	The extent to which a user adapts/reconfigures/reinvents a technology, effectively making it their own in the process. Captures user's proclivity towards experimenting with Generative AI functions
Attitude towards use	Beliefs concerning usefulness, ease of use, comfort, value, etc. offered by the technology.	**Interface Appropriation**	The extent to which a user is at ease with using the platform, as well as the degree to which a user finds it useful.
Faithfulness of Appropriation	Technology is used in a manner consistent with its intended functionality	**Ethical Appropriation**	Measure of one's ethical disposition towards Generative AI use.

dimension gauges user perceptions regarding Generative AI use that may extend beyond the intent of the developers.

6.2. Theoretical contribution

The scale advances significant theoretical contributions. Primarily, to the best of our knowledge, our GAIA scale is the first appropriation scale constructed using an extensive mixed-methods approach, drawing on prior literature, qualitative inquiry and advanced empirical analysis. A noteworthy limitation in extant literature has been the dearth of a validated GAIA measure that is anchored on individual usage rather than organisational usage. This study bridges this gap by developing the GAIA scale.

Further, the methodological rigour followed in the scale development process helps bring the scrupulousness of scientific research to social sciences. Specifically, the quantification of content validity using CVI (Polit et al., 2007) and testing of nomological validity via PLS-SEM lends novelty to this study, providing a blueprint for future scale development methodologists. Moreover, the scale improves our current understanding of GAIA and presents a new basis for gaining theoretical insight concerning its drivers and outcomes. In this study, we have also established the nomological validity and predictive validity of our GAIA scale. A plethora of research ideas can therefore be generated on the additional members of the nomological network of GAIA, i.e, agile leadership, innovation orientation and individual creative performance. By doing so, scholars will be able to advance theoretically in their specific disciplines.

6.3. Managerial implications

Our research endeavours to enlist actionable strategies that organisations and employees can adopt to draw maximum benefit from using GAI in the workplace. Harnessing the potential of Generative AI requires an understanding of appropriation levels and gap areas. The scale enables measurement of GAIA in workplaces, allowing concentrated efforts for its monitoring and improvement such that desirable business outcomes can be achieved. Generative AI can contribute a valuable strategic advantage, furnishing a work environment that is more creative and productive. Business professionals can utilise this scale to effect GAIA in organisations and plan for its effective monitoring. Since GAI has matured to a point where it is now being appropriated across the majority of the nations, the GAIA scale developed in this study is an asset for companies to adequately comprehend the appropriation level of employees. Considering that the scale emphasises adoptive and integrative appropriation dimensions, organisations can educate employees regarding the potential of GAI technologies and how they can be leveraged in everyday work lives. This can help increase interest in, and willingness to use, GAI technologies. Organisations may also create suitable training programmes for employees contingent upon their level of appropriation for the seamless integration of GAI in their practices.

Our scale also brings to light the importance of customisation when appropriating technologies. Such customisations, or workarounds, are often a covert phenomenon in organisations (Bal et al., 2022). In this regard, organisations may incentivise such novel customisations, thereby bringing this covert phenomenon into the open. Individuals may also leverage our scale to pinpoint the areas where they fall short in appropriating GAI technology.

Given that our scale emphasises interface appropriation, GAI technology developers can capitalise on it to devise a simpler, better interface for GAI and implement innovative interface modifications reliant on issues that employees encounter. Scholars can build on this research as well. Since this scale is designed for nations with collectivist cultures, there is ample room for academics to expand this research into countries with individualistic cultures. By doing so, researchers will be able to contribute to the body of knowledge by uncovering new dimensions of GAIA. Additionally, users should be equipped to provide continuous feedback to optimise appropriation at the developmental level of GAI, which is only feasible with recurring feedback. Artificial intelligence technologies, such as GAI, are projected to progress drastically in the foreseeable future; therefore, appropriation of GAI by users of these technologies will likely have notable consequences on the success of AI research.

7. Limitations and future research avenues

This study adds to the growing literature on both Generative AI and appropriation. Despite this, there remain some limitations that future studies could address.

First, the study is limited to innovation managers from Poland. Future researchers can validate the GAIA scale in a sample that is geographically or culturally distinct to ascertain universality. For instance, ethics, being a cultural factor, may vary and necessitate different appropriations based on cultural norms. Future studies can also analyse the impact of GAIA across diverse occupations, generational groups, and genders.

Second, GAIA has been conceptualised as a reflective-reflective construct, both at first and second order, based on theoretical underpinnings (MacKenzie et al., 2005) and empirical validation. While this foundation has been established in our study, and we have fulfilled all preliminary criteria, the future may witness a myriad of changes. As new GAI applications emerge, it may be necessary to incorporate additional items or dimensions into the scale. Future researchers might investigate the implications of an alternative formative model by examining additional reflective indicators.

Finally, during this study, the most widely used GAI application by consumers was ChatGPT, which we deemed a suitable representative technology type for developing our GAIA scale. A review of the items measured in the five dimensions of the GAIA scale suggests that they may also be relevant for other GAI applications. We recommend adapting and testing the GAIA scale for these other applications, also.

8. Conclusion

The widespread use of generative AI tools has shown their potential to bring about major improvements in the area of business management and to alter the work practices of those who use them. Given the wide range of practical applications provided by the technology, as well as its early stage of development, there are important considerations about how the technology may be used, necessitating an assessment of generative AI appropriation in the workplace. This article develops and validates a second-order, reflective-reflective Generative AI appropriation scale, comprising dimensions of integrative appropriation, adoptive appropriations, customised appropriation, interface appropriation and ethical appropriation. The study adopts a mixed-method approach that combines qualitative and quantitative insights from multiple studies across multiple samples. The GAIA scale developed herein offers a robust and comprehensive measure that can be used to explicate, assess, and improve the appropriation of generative AI in the workplace.

CRediT authorship contribution statement

Puja Khatri: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization, Writing – review & editing. **Harshleen Kaur Duggal:** Writing – original draft, Formal analysis, Investigation. **Asha Thomas:** Writing – original draft, Investigation, Conceptualization, Data curation, Funding acquisition, Writing – review & editing. **Vincenzo Corvello:** Validation, Conceptualization, Supervision, Writing – original draft. **Ewa Prałat:** Data curation, Formal analysis, Writing – original draft. **Atul Shiva:** Writing – original draft, Investigation, Formal analysis.

Source of funding

None.

Declaration of interest statement

The authors declare that there is no conflict of interest.

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Appendices.

Table A1
Technological Appropriation Definitions

Author & Year	Definiton
Bal et al. (2022)	"the way in which employees adopt, adapt and incorporate technologies into their existing working practices"
(Seebacher et al., 2021)	"the way technology is utilised while being impacted by normative structures surrounding an organization."
Lin et al. (2022)	"user-defined technology use, and involves using a tool, artefact, or application to support the development of one's knowledge or skills"
Benamar et al. (2020)	"the process through which the user adopts, adapts and incorporates this technology in his/her practice, work or leisure"
Bar et al. (2016)	"the process through which technology users go beyond mere adoption to make technology their own and to embed it within their social, economic, and political practices."
Mifsud et al. (2015)	"users' efforts to create their own sense of the technology"
Ylipulli et al. (2014)	"an approach in social science technology studies that strives to explain the adoption of new technologies as a part of everyday life."
Dourish (2003)	"the ways in which people adopt and adapt interactive technologies, fitting them into working practices and evolving those practices around them"

Table A2
List of retained items for data collection after CVI assessment

Items Retained for Data Collection based on I-CVI (>0.78), κ* (≥0.75), Interpretation (excellent) and S-CVI value (>0.9)																		
Items	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	N	A	N-A	UA	I-CVI	*Pc*	κ*	Interpretation
I consider Generative AI as a valuable tool that contributes to the overall success of my work.	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1	Excellent
I trust the reliability of the responses generated by Generative AI.	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1	Excellent
I feel confident that Generative AI aligns with our organization's goals.	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1	Excellent
I can validate my thought process through Generative AI	1	1	0	0	1	1	1	1	1	1	10	8	2	0	0.8	0.043945313	0.79	Excellent
I'm interested in using Generative AI functions	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1	Excellent
I'm willing to use Generative AI functions	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1	Excellent

(continued on next page)

Table A2 (*continued*)

Items Retained for Data Collection based on I-CVI (>0.78), κ* (≥0.75), Interpretation (excellent) and S-CVI value (>0.9)

Items	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	N	A	N-A	UA	I-CVI	*Pc*	κ*	Interpretation
I find insights generated by Generative AI as valuable	1	1	1	1	1	1	0	0	1	1	10	8	2	0	0.8	0.043945313	0.79	Excellent
Using Generative AI improves my effectiveness	1	1	1	0	1	1	1	1	1	0	10	8	2	0	0.8	0.043945313	0.79	Excellent
Using Generative AI allows me to help solve many queries	1	0	1	1	1	1	1	0	1	1	10	8	2	0	0.8	0.043945313	0.79	Excellent
I find Generative AI a good tool for work	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1	Excellent
I find Generative AI user-friendly	1	0	0	1	1	1	1	1	1	1	10	8	2	0	0.8	0.043945313	0.79	Excellent
Generative AI interface is very smooth	1	1	1	0	1	1	1	1	1	1	10	9	1	0	0.9	0.009765625	0.90	Excellent
I think Generative AI can be very useful shortcut for meeting deadlines	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1	Excellent
I use Generative AI in different ways even other than those originally intended by the developers	1	1	0	0	1	1	1	1	1	1	10	8	2	0	0.8	0.043945313	0.79	Excellent
I feel in control over Generative AI functions	1	1	1	0	1	1	1	0	1	1	10	8	2	0	0.8	0.043945313	0.79	Excellent
I feel comfortable experimenting with different settings of Generative AI.	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1	Excellent
I can't wait to invent new uses of Generative AI	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1	Excellent
I have modified Generative AI to leverage its potential	1	1	1	1	0	1	1	1	1	1	10	9	1	0	0.9	0.009765625	0.90	Excellent
I am invested in exploring new capabilities of Generative AI to help me complete my work tasks	1	1	1	0	1	1	1	1	1	1	10	9	1	0	0.9	0.009765625	0.90	Excellent
I proactively seek updates to ensure optimal usage of Generative AI.	0	1	1	1	1	1	1	1	0	1	10	8	2	0	0.8	0.043945313	0.79	Excellent
I think Generative AI can be used in multiple ways constructively	1	1	1	1	1	1	1	0	1	1	10	9	1	0	0.9	0.009765625	0.90	Excellent
I've modified my everyday work practices to leverage the possibilities of Generative AI	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1.00	Excellent
I integrate Generative AI seamlessly into my daily work routine.	0	1	1	1	1	0	1	1	1	1	10	8	2	0	0.8	0.043945313	0.79	Excellent
Generative AI is my personal assistant for brainstorming	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1	Excellent
I find Generative AI useful in generating creative ideas or content.	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1	Excellent
Generative AI enhances my decision-making process by providing valuable insights.	1	0	1	0	1	1	1	1	1	1	10	8	2	0	0.8	0.043945313	0.79	Excellent
Generative AI helps me to finish my work quickly	1	1	1	1	0	1	1	0	1	1	10	8	2	0	0.8	0.043945313	0.79	Excellent
Generative AI helps me enhance the quality of my work reports.	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1	Excellent
I rely on Generative AI as a valuable resource to expand my knowledge.	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1	Excellent
Generative AI helps me develop problem-solving skills	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1	Excellent
My organization has provided training and/or resources to help me effectively utilise Generative AI tools	1	1	0	1	1	1	1	1	1	0	10	8	2	0	0.8	0.043945313	0.79	Excellent
My organization provides ongoing support to stay updated with advancements in Generative AI tools	1	1	1	1	0	1	1	1	1	1	10	9	1	0	0.9	0.009765625	0.90	Excellent
I have redefined usage of Generative AI to my benefit	1	1	0	1	1	1	1	0	1	1	10	8	2	0	0.8	0.043945313	0.79	Excellent

(*continued on next page*)

Table A2 (*continued*)

Items	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	N	A	N-A	UA	I-CVI	*Pc*	κ*	Interpretation
Items Retained for Data Collection based on I-CVI (>0.78), κ* (≥0.75), Interpretation (excellent) and S-CVI value (>0.9)																		
I understand the ethical considerations when using Generative AI tools	1	1	1	1	1	1	0	1	0	1	10	8	2	0	0.8	0.043945313	0.79	Excellent
I think it is okay to improperly use Generative AI if it suits the organization	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1	Excellent
I think it is okay to use technology to suit to your benefit	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1	Excellent
I think it is okay to use Generative AI even beyond its general intent	1	1	1	1	1	1	1	1	1	1	10	10	0	1	1	0.000976563	1	Excellent
															18	33.7		
																Total No of Items		37
																S-CVI/Ave (through ICVI)		0.911

Notes: N = Total number of experts. A = Number of experts in agreement for a specific item. N-A = Difference between the total number of experts (N) and the number of experts in agreement (A). UA = Universal agreement – Items that gained consensus with a relevance rating of 3 or 4 from all experts. I-CVI: Item-level content validity index – Calculated by dividing the number of experts in agreement by the total number of experts for each item. *Pc*: Probability of chance agreement – The likelihood that the agreement among experts occurred merely by chance. κ* = Modified Kappa – A statistical measure used to adjust for the possibility of chance agreement among the experts. S-CVI/Ave = Scale-level content validity index (average method) – Computed by taking the average of I-CVI scores for all items.

Table A3
Sample Demographics

Demographic variables	Study 2 (n = 106)		Study 3 & 4 (n = 671)		Study 5			
					Italy (n = 157)		India (n = 238)	
	Actual	%	Actual	%	Actual	%	Actual	%
Age (in years)								
Below 25 years	6	5.7	62	9.2	8	5.1	38	16.0
26–30	17	16.0	101	15.1	19	12.1	70	29.4
31–35	19	17.9	110	16.4	26	16.6	36	15.1
36–40	23	21.7	129	19.2	28	17.8	29	12.2
41–45	16	15.1	90	13.4	17	10.8	19	8.0
46–50	10	9.4	72	10.7	25	15.9	16	6.7
51 and above	15	14.2	107	15.9	34	21.7	30	12.6
Gender								
Female	53	50.0	354	52.8	61	38.9	111	46.6
Male	53	50.0	317	47.2	96	61.1	127	53.4
Country of Residence								
Italy	–	–	–	–	157	100.0	–	–
Poland	106	100.0	671	100.0	–	–	–	–
India	–	–	–	–	–	–	238	100.0
Level of Management								
Middle Level Managers	81	76.4	495	73.8	112	71.3	181	76.1
Top Level Managers	25	23.6	176	26.2	45	28.7	57	23.9
Total Job Experience								
1–5 years	31	29.2	151	22.5	34	21.7	71	29.8
6–10 years	25	23.6	183	27.3	37	23.6	76	31.9
11–15 years	18	17.0	104	15.5	21	13.4	36	15.1
16–20 years	13	12.3	67	10.0	22	14.0	18	7.6
More than 20 years	19	17.9	166	24.7	43	27.4	37	15.5
Sector of Employment								
Consulting	18	17.0	98	14.6	29	18.5	22	9.2
Education	20	18.9	107	15.9	22	14.0	40	16.8
IT	19	17.9	104	15.5	51	32.5	76	31.9
Marketing and Advertising	6	5.7	60	8.9	16	10.2	17	7.1
Healthcare	9	8.5	69	10.3	14	8.9	16	6.7
Manufacturing	34	32.1	233	34.7	25	15.9	67	28.2

Table A4
Cross Loadings

Indicators	IA	AA	CUA	IFA	EA
CGA_IA_2	0.90	0.76	0.79	0.71	0.68
CGA_IA_5	0.91	0.75	0.80	0.70	0.67
CGA_IA_6	0.90	0.75	0.76	0.69	0.66
CGA_IA_9	0.85	0.70	0.74	0.61	0.61
CGA_AA_1	0.74	0.93	0.70	0.74	0.60
CGA_AA_2	0.76	0.94	0.72	0.74	0.63
CGA_AA_5	0.80	0.90	0.75	0.69	0.66
CGA_CUA_1	0.68	0.55	0.83	0.68	0.58
CGA_CUA_2	0.70	0.71	0.82	0.69	0.61
CGA_CUA_3	0.78	0.68	0.88	0.78	0.60
CGA_CUA_4	0.70	0.65	0.83	0.70	0.62
CGA_CUA_5	0.76	0.75	0.86	0.78	0.67
CGA_CUA_6	0.78	0.63	0.86	0.57	0.60
CGA_IFA_1	0.74	0.76	0.72	0.90	0.63
CGA_IFA_2	0.60	0.60	0.64	0.85	0.52
CGA_IFA_3	0.64	0.68	0.64	0.88	0.56
CGA_EA_1	0.61	0.64	0.59	0.67	0.83
CGA_EA_2	0.67	0.56	0.67	0.47	0.85
CGA_EA_3	0.60	0.55	0.60	0.54	0.89

Data availability

Data will be made available on request.

References

Ahmad, A.B., Liu, B., Butt, A.S., 2020. Scale development and construct clarification of change recipient proactivity. Pers. Rev. 49 (8), 1619–1635. https://doi.org/10.1108/PR-02-2019-0091.

Almanasreh, E., Moles, R., Chen, T.F., 2019. Evaluation of methods used for estimating content validity. In: Research in Social and Administrative Pharmacy, 15. Elsevier Inc, pp. 214–221. https://doi.org/10.1016/j.sapharm.2018.03.066, 2.

Andreessen, Horowitz, 2023. How are consumers using generative AI? https://a16z.com/how-are-consumers-using-generative-ai/.

Astrachan, C.B., Patel, V.K., Wanzenried, G., 2014. A comparative study of CB-SEM and PLS-SEM for theory development in family firm research. Journal of Family Business Strategy 5 (1), 116–128. https://doi.org/10.1016/j.jfbs.2013.12.002.

Backlinko, 2024. ChatGPT/OpenAI statistics: how many people use ChatGPT? https://backlinko.com/chatgpt-stats.

Bagozzi, R.P., Yi, Y., 1988. On the evaluation of structural equation models. J. Acad. Market. Sci. 16 (1), 74–94. https://doi.org/10.1007/BF02723327.

Bal, M., Benders, J., Vermeerbergen, L., 2022. 'Bringing the covert into the open': a case Study on technology appropriation and continuous improvement. Int. J. Environ. Res. Publ. Health 19 (10). https://doi.org/10.3390/ijerph19106333.

Bar, F., Weber, M.S., Pisani, F., 2016. Mobile technology appropriation in a distant mirror: baroquization, creolization, and cannibalism. New Media Soc. 18 (4), 617–636. https://doi.org/10.1177/1461444816629474.

Barrett, A.K., 2018. Technological appropriations as workarounds: integrating electronic health records and adaptive structuration theory research. Inf. Technol. People 31 (2), 368–387. https://doi.org/10.1108/ITP-01-2016-0023.

Bartlett, M.S., 1950. Tests of significance in factor analysis. British Journal of Statistical Psychology 3 (2), 77–85. https://doi.org/10.1111/j.2044-8317.1950.tb00285.x.

Beaudry, A., Pinsonneault, A., Pinsonneault, B., User, Molson, J., Ca, C.A.P., 2005. Understanding user responses to information technology: a coping model of user adaptation responses to IT arterly understanding user responses to information technology: a coping model of user Adaptation1. Source: MIS Q. 29 (3).

Becker, J.-M., Klein, K., Wetzels, M., 2012. Hierarchical latent variable models in PLS-SEM: guidelines for using reflective-formative type models. Long. Range Plan.: International Journal of Strategic Management 45 (5–6), 359–394. https://doi.org/10.1016/j.lrp.2012.10.001.

Becker, J.-M., Cheah, J.-H., Gholamzade, R., Ringle, C.M., Sarstedt, M., 2023. PLS-SEM's most wanted guidance. Int. J. Contemp. Hospit. Manag. 35 (1), 321–346. https://doi.org/10.1108/IJCHM-04-2022-0474.

Benamar, L., Balagué, C., Zhong, Z., 2020. Internet of Things devices appropriation process: the Dynamic Interactions Value Appropriation (DIVA) framework. Technovation 89. https://doi.org/10.1016/j.technovation.2019.06.001.

Biswas, S.S., 2023. Role of chat GPT in public health. In: Annals of Biomedical Engineering, 51. Springer, pp. 868–869. https://doi.org/10.1007/s10439-023-03172-7, 5.

Bollen, K.A., Ting, K.F., 2000. A tetrad test for causal indicators. Psychol. Methods 5 (1), 3–22. https://doi.org/10.1037/1082-989X.5.1.3.

Booyse, D., Scheepers, C.B., 2024. Barriers to adopting automated organisational decision-making through the use of artificial intelligence. Manag. Res. Rev. 47 (1), 64–85. https://doi.org/10.1108/MRR-09-2021-0701.

Brown, O., Davison, R.M., Decker, S., Ellis, D.A., Faulconbridge, J., Gore, J., Greenwood, M., Islam, G., Lubinski, C., MacKenzie, N.G., Meyer, R., Muzio, D., Quattrone, P., Ravishankar, M.N., Zilber, T., Ren, S., Sarala, R.M., Hibbert, P., 2024. Theory-Driven perspectives on generative artificial intelligence in business and management. Br. J. Manag. 35 (1), 3–23. https://doi.org/10.1111/1467-8551.12788.

Browne, M.W., Cudeck, R., 1992. Alternative ways of assessing model fit. Socio. Methods Res. 21 (2), 230–258. https://doi.org/10.1177/0049124192021002005.

Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G.J., Beltran, J.R., Boselie, P., Lee Cooke, F., Decker, S., DeNisi, A., Dey, P.K., Guest, D., Knoblich, A.J., Malik, A., Paauwe, J., Papagiannidis, S., Patel, C., Pereira, V., Ren, S., et al., 2023. Human resource management in the age of generative artificial intelligence: perspectives and research directions on ChatGPT. Hum. Resour. Manag. J. 33 (3), 606–659. https://doi.org/10.1111/1748-8583.12524.

Burger, B., Kanbach, D.K., Kraus, S., Breier, M., Corvello, V., 2023. On the use of AI-based tools like ChatGPT to support management research. Eur. J. Innovat. Manag. 26 (7), 233–241. https://doi.org/10.1108/EJIM-02-2023-0156.

Carroll, J., Howard, S., Peck, J., Murphy, J., 2003. from adoption to use: the process of appropriating a mobile phone.

Carvalho, I., Ivanov, S., 2023. ChatGPT for tourism: applications, benefits and risks. Tour. Rev. https://doi.org/10.1108/TR-02-2023-0088. *ahead-of-print*(ahead-of-print).

Cascio, W.F., Montealegre, R., 2016. How technology is changing work and organizations. In: Annual Review of Organizational Psychology and Organizational Behavior, 3. Annual Reviews Inc, pp. 349–375. https://doi.org/10.1146/annurev-orgpsych-041015-062352.

Chin, W.W., Gopal, A., Salisbury, W.D., Salisbury, W David, 1997. Advancing the theory of adaptive structuration: the development of a Scale to measure faithfulness of appropriation, 8 (Issue 4).

Chui, M., Roberts, R., Yee, L., 2022. Generative AI is Here: How Tools like Chatgpt could Change your Business.

Churchill, G.A., 1979. A paradigm for developing better measures of Marketing Constructs. J. Mark. Res. 16, 64–73.

Cimino, A., Felicetti, A.M., Corvello, V., Ndou, V., Longo, F., 2024. Generative artificial intelligence (AI) tools in innovation management: a study on the appropriation of ChatGPT by innovation managers. Manag. Decis. https://doi.org/10.1108/MD-10-2023-1968.

Costello, A.B., Osborne, J.W., 2005. Best practices in exploratory factor analysis: four recommendations for getting the most from your analysis. Practical Assess. Res. Eval. 10. http://www.statsoft.com/textbook/.

Dahmen, J., Kayaalp, M.E., Ollivier, M., Pareek, A., Hirschmann, M.T., Karlsson, J., Winkler, P.W., 2023. Artificial intelligence bot ChatGPT in medical research: the potential game changer as a double-edged sword. In: Knee Surgery, Sports Traumatology, Arthroscopy, 31. Springer Science and Business Media Deutschland GmbH, pp. 1187–1189. https://doi.org/10.1007/s00167-023-07355-6, 4.

Dash, G., Paul, J., 2021. CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. Technological Forecasting & Social Change/Technological Forecasting and Social Change 173, 121092. https://doi.org/10.1016/j.techfore.2021.121092.

Davis, F., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 13 (3), 319. https://doi.org/10.2307/249008.

Davis, L.L., 1992. Instrument Review: Getting the Most from a Panel of Experts.

Davison, R.M., Laumer, S., Tarafdar, M., Wong, L.H.M., 2023. Pickled eggs: generative AI as research assistant or co-author?. In: Information Systems Journal, 33. John Wiley and Sons Inc, pp. 989–994. https://doi.org/10.1111/isj.12455, 5.

DeSanctis, G., Poole, M.S., 1994. Capturing the complexity in advanced technology use: adaptive structuration theory. Organ. Sci. 5 (2), 121–147. https://doi.org/10.1287/orsc.5.2.121.
DeVellis, R.F., 2017. Scale Development: Theory and Applications.
Dey, B.L., Binsardi, B., Prendergast, R., Saren, M., 2013. A qualitative enquiry into the appropriation of mobile telephony at the bottom of the pyramid. Int. Mark. Rev. 30 (4), 297–322. https://doi.org/10.1108/IMR-03-2012-0058.
Dourish, P., 2003. The appropriation of interactive technologies: some lessons from placeless documents. In: Computer Supported Cooperative Work, 12.
Duarte, F., 2023. Number of Chatgpt Users (2023). Exploding Topics.
Dwivedi, Y.K., Kshetri, N., Hughes, L., Slade, E.L., Jeyaraj, A., Kar, A.K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M.A., Al-Busaidi, A.S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., et al., 2023. "So what if ChatGPT wrote it?" multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. Int. J. Inf. Manag. 71. https://doi.org/10.1016/j.ijinfomgt.2023.102642.
Earnest Analytics, 2024. AI Series Part 3: ChatGPT and Anthropic top paid AI Tools by retention. https://www.earnestanalytics.com/insights/chatgpt-and-anthropic-top-paid-ai-tools-by-retention.
Eynon, R., 2021. Becoming digitally literate: reinstating an educational lens to digital skills policies for adults. Br. Educ. Res. J. 47 (1), 146–162. https://doi.org/10.1002/berj.3686.
Field, A.P., 2013. *Discovering Statistics Using SPSS* (Fourth). Sage Publications.
Finn, A., Kayandé, U., 1997. Reliability assessment and optimization of marketing measurement. In source: journal of marketing research, 34 (2).
Gartner, 2022. *Understanding GenAI*. Gartner. https://www.gartner.com/en/topics/generative-ai/.
Gaskin, J., Lyytinen, K., 2012. Psychological ownership and the individual appropriation of technology. Information Systems Theory: Explaining and Predicting Our Digital Society 2, 25–39.
Gefen, D., Straub, D., 2005. A practical guide to factorial validity using PLS-Graph: Tutorial and annotated example. Commun. Assoc. Inf. Syst. 16. https://doi.org/10.17705/1cais.01605.
Gold, A.H., Malhotra, A., Segars, A.H., 2001. Knowledge management: an organizational capabilities perspective. J. Manag. Inf. Syst. 18 (1), 185–214. https://doi.org/10.1080/07421222.2001.11045669.
Grech, A., Mehnen, J., Wodehouse, A., 2023. An extended AI-Experience: industry 5.0 in creative product innovation. In sensors. MDPI 23 (6). https://doi.org/10.3390/s23063009.
Hair, J.F., Black, W., Babin, B., Anderson, R., 2010. Multivariate data analysis: a global perspective. In: Multivariate Data Analysis: a Global Perspective.
Hair, J.F., Risher, J.J., Sarstedt, M., Ringle, C.M., 2019. When to use and how to report the results of PLS-SEM. Eur. Bus. Rev. 31 (1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203.
Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M., 2021. Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), second ed. Springer International Publishing.
Heblich, B., Terzidis, O., M, M.G., Kuschel, K., Mukadam, M., Birkenbach, M., 2023. Living well: empirically developed structural equation model for healthy and effective self-regulation. Int. J. Clin. Health Psychol. 23 (4), 100375. https://doi.org/10.1016/j.ijchp.2023.100375.
Hinkin, T.R., 1998. A brief tutorial on the development of measures for use in survey questionnaires. Organ. Res. Methods 1 (1), 104–121.
Hu, K., 2023. Chatgpt Sets Record for fastest-growing User Base - Analyst Note. Reuters.
Hu, L., Bentler, P.M., 1999. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. Struct. Equ. Model. 6 (1), 1–55. https://doi.org/10.1080/10705519909540118.
Hussenot, A., 2008. Between structuration and translation: an approach of ICT appropriation. J. Organ. Change Manag. 21 (3), 335–347. https://doi.org/10.1108/09534810810874813.
Jarvis, C.B., Mackenzie, S.B., Podsakoff, P.M., Giliatt, N., Mee, J.F., 2003. A critical review of construct indicators and measurement model misspecification in marketing and consumer research. J. Consum. Res. 30 (2), 199–218. https://doi.org/10.1086/376806.
Kaiser, H.F., Rice, J., 1974. Little jiffy, mark IV. Educ. Psychol. Meas. 34 (1), 111–117.
Kang, S., Lim, K.H., Kim, M.S., Yang, H.D., 2012. A multilevel analysis of the effect of group appropriation on collaborative technologies use and performance. Inf. Syst. Res. 23 (1), 214–230. https://doi.org/10.1287/isre.1100.0342.
Kirk, C.P., Swain, S.D., Gaskin, J.E., 2015. I'M PROUD OF it. Source: J. Market. Theor. Pract. 23 (2), 166–184. https://doi.org/10.2307/48540561.
Ko, E.J., Kim, A.H., Kim, S.S., 2021. Toward the understanding of the appropriation of ICT-based Smart-work and its impact on performance in organizations. Technol. Forecast. Soc. Change 171. https://doi.org/10.1016/j.techfore.2021.120994.
Koc, E., Hatipoglu, S., Kivrak, O., Celik, C., Koc, K., 2023. Houston, we have a problem!: the use of ChatGPT in responding to customer complaints. Technol. Soc. 74, 102333. https://doi.org/10.1016/j.techsoc.2023.102333.
Kock, F., Berbekova, A., Assaf, A.G., Josiassen, A., 2024. Developing a scale is not enough: on the importance of nomological validity. Int. J. Contemp. Hospit. Manag. https://doi.org/10.1108/IJCHM-07-2023-1078.
Kovacic, D., 2018. Using the content validity index to determine content validity of an instrument assessing health care providers' general knowledge of human trafficking. Journal of Human Trafficking 4 (4), 327–335. https://doi.org/10.1080/23322705.2017.1364905.
Kumar, P., Sharma, S.K., Dutot, V., 2023. Artificial intelligence (AI)-enabled CRM capability in healthcare: the impact on service innovation. Int. J. Inf. Manag. 69, 102598. https://doi.org/10.1016/j.ijinfomgt.2022.102598.
Kummitha, R.K.R., 2020. Why distance matters: the relatedness between technology development and its appropriation in smart cities. Technol. Forecast. Soc. Change 157, 120087. https://doi.org/10.1016/j.techfore.2020.120087.
Li, N., Yan, Y., Yang, Y., Gu, A., 2022. Artificial intelligence capability and organizational creativity: the role of knowledge sharing and organizational cohesion. Front. Psychol. 13. https://doi.org/10.3389/fpsyg.2022.845277.
Lim, W.M., 2024. A typology of validity: content, face, convergent, discriminant, nomological and predictive validity. Journal of Trade Science 12 (3), 155–179. https://doi.org/10.1108/jts-03-2024-0016.
Lim, W.M., Gunasekara, A., Pallant, J.L., Pallant, J.I., Pechenkina, E., 2023. Generative AI and the future of education: ragnarök or reformation? A paradoxical perspective from management educators. Int. J. Manag. Educ. 21 (2), 100790. https://doi.org/10.1016/j.ijme.2023.100790.
Lin, V., Liu, G.Z., Hwang, G.J., Chen, N.S., Yin, C., 2022. Outcomes-based appropriation of context-aware ubiquitous technology across educational levels. In: Interactive Learning Environments, 30. Routledge, pp. 1515–1538. https://doi.org/10.1080/10494820.2019.1703012, 8.
Lindell, M.K., Whitney, D.J., 2001. Accounting for common method variance in cross-sectional research designs. J. Appl. Psychol. 86 (1), 114–121. https://doi.org/10.1037/0021-9010.86.1.114.
Loh, Y.A.C., Chib, A., 2019. Tackling social inequality in development: beyond access to appropriation of ICTs for employability. Inf. Technol. Dev. 25 (3), 532–551. https://doi.org/10.1080/02681102.2018.1520190.
Loh, Y.A.C., Chib, A., 2022. Reconsidering the digital divide: an analytical framework from access to appropriation. Inf. Technol. People 35 (2), 647–676. https://doi.org/10.1108/ITP-09-2019-0505.
Lund, B.D., Wang, T., 2023. Chatting about ChatGPT: how may AI and GPT impact academia and libraries?. In: Library Hi Tech News, 40. Emerald Publishing, pp. 26–29. https://doi.org/10.1108/LHTN-01-2023-0009, 3.
Lynn, M., 1986. Determination and quantification of content validity. Nurs. Res. 35 (6), 382–386.
Mackay, H., Gillespie, G., 1992. Extending the social shaping of technology approach: ideology and appropriation. Soc. Stud. Sci. 22 (4), 685–716. https://doi.org/10.1177/030631292022004006.
MacKenzie, D., Wajcman, J., 1999. The Social Shaping of Technology. Open university press.
MacKenzie, S.B., Podsakoff, P.M., Jarvis, C.B., 2005. The problem of measurement model misspecification in behavioral and organizational research and some recommended solutions. J. Appl. Psychol. 90 (4), 710–730.
Mendy, J., Jain, A., Thomas, A., 2025. Artificial intelligence in the workplace–challenges, opportunities and HRM framework: a critical review and research agenda for change. J. Manag. Psychol. 40 (5), 517–538.
Mifsud, M., Cases, A.S., N'Goala, G., 2015. Service appropriation: how do customers make the service their own? J. Serv. Manag. 26 (5), 706–725. https://doi.org/10.1108/JOSM-04-2015-0136.
Mikalef, P., Gupta, M., 2021. Artificial intelligence capability: conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Inf. Manag. 58 (3). https://doi.org/10.1016/j.im.2021.103434.
Moura, E. O. de, Bispo, M. de S., 2020. Sociomateriality: theories, methodology, and practice. Canadian Journal of Administrative Sciences 37 (3), 350–365. https://doi.org/10.1002/cjas.1548.
Mutonyi, B.R., Slåtten, T., Lien, G., 2020. Organizational climate and creative performance in the public sector. Eur. Bus. Rev. 32 (4), 615–631. https://doi.org/10.1108/EBR-02-2019-0021.
Netemeyer, R.G., Bearden, W.O., Sharma, S., 2003. Scaling Procedures: Issues and Applications.
Noor, N., Rao Hill, S., Troshani, I., 2022. Developing a service quality scale for artificial intelligence service agents. Eur. J. Market. 56 (5), 1301–1336. https://doi.org/10.1108/EJM-09-2020-0672.
Nunnally, J.C., Bernstein, I.R., 1978. Psychometric theory. In: Psychometric Theory. Tata McGraw Hill).
Orlikowski, W.J., 2000. Using technology and constituting structures: a practice lens for studying technology in organizations. https://www.jstor.org/stable/2640412.
Orlikowski, W.J., Barley, S.R., 2001. Technology and institutions: what can research on information technology and research on organizations learn from each other? MIS Q. 25 (2), 145. https://doi.org/10.2307/3250927.
Papadas, K.K., Avlonitis, G.J., Carrigan, M., 2017. Green marketing orientation: conceptualization, scale development and validation. J. Bus. Res. 80, 236–246. https://doi.org/10.1016/j.jbusres.2017.05.024.
Paul, J., Lim, W.M., O'Cass, A., Hao, A.W., Bresciani, S., 2021. Scientific procedures and rationales for systematic literature reviews (SPAR-4-SLR). Int. J. Consum. Stud. 45, 1–16. https://doi.org/10.1111/ijcs.12695.
Pinch, T.J., Bijker, W.E., 1984. The social construction of facts and artefacts: or how the sociology of science and the sociology of technology might benefit each other. Soc. Stud. Sci. 14 (3), 399–441. https://doi.org/10.1177/030631284014003004.
Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y., Podsakoff, N.P., 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. J. Appl. Psychol. 88 (5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879.
Podsakoff, P.M., MacKenzie, S.B., Podsakoff, N.P., 2012. Sources of method bias in social science research and recommendations on how to control it. Annu. Rev. Psychol. 63, 539–569. https://doi.org/10.1146/annurev-psych-120710-100452.

Polit, D.F., Beck, C.T., 2006. The content validity index: are you sure you know what's being reported? Critique and recommendations. Res. Nurs. Health 29 (5), 489–497. https://doi.org/10.1002/nur.20147.

Polit, D.F., Beck, C.T., Owen, S.V., 2007. Focus on research methods: is the CVI an acceptable indicator of content validity? Appraisal and recommendations. Res. Nurs. Health 30 (4), 459–467. https://doi.org/10.1002/nur.20199.

Poole, M., DeSanctis, G., 1989. Use of group decision support systems as an appropriation process. *[1989]*. Proceedings of the Twenty-Second Annual Hawaii International Conference on System Sciences. Volume IV: Emerging Technologies and Applications Track 4, 149–157. https://doi.org/10.1109/HICSS.1989.48152, 4.

Poole, M., DeSanctis, G., 1990. Understanding the use of Group decision support systems: the theory of adaptive structuration. In: Organizations and Communication Technology. SAGE Publications, Inc, pp. 173–193. https://doi.org/10.4135/9781483325385.n8.

Ritala, P., Ruokonen, M., Ramaul, L., 2023. Transforming boundaries: how does ChatGPT change knowledge work? J. Bus. Strat. https://doi.org/10.1108/JBS-05-2023-0094.

Rossiter, J.R., 2002. The C-OAR-SE procedure for scale development in marketing. Int. J. Res. Market. 19 (2002), 305–335. www.elsevier.com/locate/ijresmar.

Salisbury, W.D., Chin, W.W., Gopal, A., Newsted, P.R., Bauer, C.T., 2002. Measurement-Developing a Scale to capture consensus on appropriation. http://about.jstor.org/terms.

Sarstedt, M., Hair, J.F., Cheah, J.H., Becker, J.M., Ringle, C.M., 2019. How to specify, estimate, and validate higher-order constructs in PLS-SEM. Australas. Market J. 27 (3), 197–211. https://doi.org/10.1016/j.ausmj.2019.05.003.

Sarstedt, M., Ringle, C.M., Hair, J.F., 2021. Partial least squares structural equation modeling. In: Homburg, C., Klarmann, M., Vomberg, A. (Eds.), Handbook of Market Research. Springer, Issue July, pp. 1–47. https://doi.org/10.1007/978-3-319-05542-8.

Sætra, H.S., 2023. Generative AI: here to stay, but for good? Technol. Soc. 75. https://doi.org/10.1016/j.techsoc.2023.102372.

Saviano, M., Thomas, A., Del Prete, M., Verderese, D., Sasso, P., 2025. The impact of new generative AI chatbots on the switch point (SP): toward an artificial emotional awareness (AEA). Eur. J. Innovat. Manag. 28 (5), 2029–2053. https://doi.org/10.1108/EJIM-05-2024-0520, 5 August 2025.

Schmitz, K.W., Teng, J.T.C., Webb, K.J., 2016. Capturing the complexity of malleable IT use: adaptive structuration theory for individuals. MIS Q. 40 (3), 663–686. https://doi.org/10.25300/MISQ/2016/40.3.07.

Shiva, A., Kushwaha, B.P., Rishi, B., 2023. A model validation of robo-advisers for stock investment. Borsa Istanbul Review 23 (6), 1458–1473. https://doi.org/10.1016/j.bir.2023.09.005.

Simmering, M.J., Fuller, C.M., Richardson, H.A., Ocal, Y., Atinc, G.M., 2015. Marker variable choice, reporting, and interpretation in the detection of common method variance: a review and demonstration. Organ. Res. Methods 18 (3), 473–511. https://doi.org/10.1177/1094428114560023.

Stadler, C., Reeves, M., 2023. Three Lessons from Chatting About Strategy with Chatgpt. MIT Sloan Management Review.

Thomas, A., 2024. Digitally transforming the organization through knowledge management: a socio-technical system (STS) perspective. Eur. J. Innovat. Manag. 27 (9), 437–460. https://doi.org/10.1108/EJIM-02-2024-0114.

Thomas, A., Duggal, H.K., Khatri, P., Corvello, V., 2024a. ChatGPT appropriation: a catalyst for creative performance, innovation orientation, and agile leadership. Technol. Soc. 78, 102619.

Thomas, A., Khatri, P., Dabas, V., Coniglio, I.M., 2024b. Capturing innovation orientation in knowledge workers: development and validation of a measurement scale. J. Knowl. Manag. https://doi.org/10.1108/JKM-12-2023-1276.

Voorhees, C.M., Brady, M.K., Calantone, R., Ramirez, E., 2016. Discriminant validity testing in marketing: an analysis, causes for concern, and proposed remedies. J. Acad. Market. Sci. 44 (1), 119–134. https://doi.org/10.1007/s11747-015-0455-4.

Waltz, C., Lea Strickland, O., Lenz, E., 2010. Measurement in Nursing and Health Research.

Wetzels, M., Odekerken-Schröder, G., Van Oppen, C., Odekerken-Schr, G., Portal, S., 2009. Using PLS path modeling for Assessing Hierarchical Construct Models: guidelines and empirical illustration. Source: MIS Q. 33 (1), 177–195.

Williams, R., Edge, D., 1996. The social shaping of technology. In: Research Policy, 25. ELSEVIER.

Wirth, W., Von Pape, T., Karnowski, V., 2008. An integrative model of mobile phone appropriation. J. Computer-Mediated Commun. 13 (3), 593–617. https://doi.org/10.1111/j.1083-6101.2008.00412.x.

Yi, M.Y., Fiedler, K.D., Park, J.S., 2006. Understanding the role of individual innovativeness in the acceptance of IT-Based innovations: comparative analyses of models and measures. In: The Author Journal Compilation C, 37. Decision Sciences Institute.

Ylipulli, J., Suopajärvi, T., Ojala, T., Kostakos, V., Kukka, H., 2014. Municipal WiFi and interactive displays: appropriation of new technologies in public urban spaces. Technol. Forecast. Soc. Change 89, 145–160. https://doi.org/10.1016/j.techfore.2013.08.037.

Yusoff, M.S.B., 2019. ABC of content validation and content validity index calculation. Education in Medicine Journal 11 (2), 49–54. https://doi.org/10.21315/eimj2019.11.2.6.

Zamani, E.D., Pouloudi, N., Giaglis, G.M., Wareham, J., 2022. Appropriating information technology artefacts through trial and error: the case of the tablet. Inf. Syst. Front. 24 (1), 97–119. https://doi.org/10.1007/s10796-020-10067-8.

Zhou, H., 2022. Generative Artificial Intelligence: a Social Construction of Technology Perspective.

Zhou, J., George, J.M., 2001. When job dissatisfaction leads to creativity: encouraging the expression of voice. In source: the Academy of Management journal. https://www.jstor.org/stable/3069410.